The Selection and Evaluation of a Sensory Technology for Interaction in a Warehouse Environment

S. A. S. Saleh Zadeh

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Seyed Amirsaleh Saleh Zadeh

Supervisor: Prof A. P. Calitz

Co-Supervisor: Prof J. H. Greyling

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In God I trust.

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Summary

In recent years, Human-Computer Interaction (HCI) has become a significant part of modern life as it has improved human performance in the completion of daily tasks in using computerised systems. The increase in the variety of bio-sensing and wearable technologies on the market has propelled designers towards designing more efficient, effective and fully natural User-Interfaces (UI), such as the Brain-Computer Interface (BCI) and the Muscle-Computer Interface (MCI). BCI and MCI have been used for various purposes, such as controlling wheelchairs, piloting drones, providing alphanumeric inputs into a system and improving sports performance.

Various challenges are experienced by workers in a warehouse environment. Because they often have to carry objects (referred to as hands-full) it is difficult to interact with traditional devices. Noise undeniably exists in some industrial environments and it is known as a major factor that causes communication problems. This has reduced the popularity of using verbal interfaces with computer applications, such as Warehouse Management Systems. Another factor that effects the performance of workers are action slips caused by a lack of concentration during, for example, routine picking activities. This can have a negative impact on job performance and allow a worker to incorrectly execute a task in a warehouse environment.

This research project investigated the current challenges workers experience in a warehouse environment and the technologies utilised in this environment. The latest automation and identification systems and technologies are identified and discussed, specifically the technologies which have addressed known problems.

Sensory technologies were identified that enable interaction between a human and a computerised warehouse environment. Biological and natural behaviours of humans which are applicable in the interaction with a computerised environment were described and discussed. The interactive behaviours included the visionary, auditory, speech production and physiological movement where other natural human behaviours such paying attention, action slips and the action of counting items were investigated. A number of modern sensory technologies, devices and techniques for HCI were identified with the aim of selecting and evaluating an appropriate sensory technology for MCI.

MCI technologies enable a computer system to recognise hand and other gestures of a user, creating means of direct interaction between a user and a computer as they are able to detect specific features extracted from a specific biological or physiological activity. Thereafter, Machine Learning (ML) is applied in order to train a computer system to detect these features and convert them to a computer interface.

An application of biomedical signals (bio-signals) in HCI using a MYO Armband for MCI is presented. An MCI prototype (MCIp) was developed and implemented to allow a user to provide input to an HCI, in a *hands-free* and *hands-full* situation. The MCIp was designed and developed to recognise the hand-finger gestures of a person when both hands are free or when holding an object, such a cardboard box. The MCIp applies an Artificial Neural Network (ANN) to classify features extracted from the surface Electromyography signals acquired by the MYO Armband around the forearm muscle.

The MCIp provided the results of data classification for gesture recognition to an accuracy level of 34.87% with a hands-free situation. This was done by employing the ANN. The MCIp, furthermore, enabled users to provide numeric inputs to the MCIp system *hands-full* with an accuracy of 59.7% after a training session for each gesture of only 10 seconds. The results were obtained using eight participants. Similar experimentation with the MYO Armband has not been found to be reported in any literature at submission of this document.

Based on this novel experimentation, the main contribution of this research study is a suggestion that the application of a MYO Armband, as a commercially available muscle-sensing device on the market, has the potential as an MCI to recognise the finger gestures *hands-free* and *hands-full*. An accurate MCI can increase the efficiency and effectiveness of an HCI tool when it is applied to different applications in a warehouse where noise and hands-full activities pose a challenge. Future work to improve its accuracy is proposed.

Keywords: Muscle-Computer Interface, MYO Armband, Artificial Neural Network.

Declaration of Own Work

I, Seyed Amirsaleh Saleh Zadeh, 213457989, hereby declare that the dissertation, Human-Computer Interaction Using Sensory Technologies in a Warehouse Environment, for MCom Computer Science and Information Systems is my own work and that is has not previously been submitted for assessment or completion of any postgraduate qualification to another University or for another Qualification.

Mr Seyed Amirsaleh Saleh Zadeh

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List of Acronyms and Abbreviations

Acronyms	Term in Full
6-DoF	Six Degrees of Freedom
AGV	Automated Guided Vehicle
API	Application Programming Interface
AR	Augmented Reality
ASA	Auditory Selective Attention
AS/RS	Automated Storage and Retrieval Systems
ASR	Automatic Speech Recognition
BCI	Brain-Computer Interface
DSR	Design Science Research
ECG	Electrocardiography
EEG	Electroencephalogram
EMG	Electromyography
EPSD	Extreme Programming Software Development
ERP	Enterprise Resource Planning
fMRI	Functional Magnetic Resonance Imaging
GPU	Graphics Processing Unit
Hz	Hertz
HCI	Human-Computer Interaction
HU	Holding Unit
HUD	Head-Up Display
IMU	Inertial Measurement Unit
IS	Information System
IT	Information Technology
LED	Light-Emitting Diode
MEMS	Micro-Electro-Mechanical System
MCI	Muscle-Computer Interface
ms	Millisecond
MMH	Manual Materials Handling
MSE	Mean Squared Error
MVP	Mean Value of Predictions
OS	Operating System

RF	Radio Frequency
RMSE	Root-Mean-Square Error
Rprop	Resilient backpropagation
SDK	Software Development Kit
SRate	Sample Rate
VEP	Visual Evoked Potential
VR	Virtual Reality
WMS	Warehouse Management System

Chapter 1. Introduction

Objective(s) of Chapter

1. *Introducing the research study.*
2. *Identifying the existing problems.*
3. *Setting the objectives for the research study.*
4. *Outlining the structure of the dissertation.*

Structural Overview of the Chapter

Chapter 1:Introduction

1.1 Background
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Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems

Chapter 5: Sensory Technologies for Human-Computer Interaction

Chapter 6: Design and Evaluation of the Solution

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1.1 Background

Effective management of industries can provide new opportunities in the supply chain in the global market. For instance, in order to manage daily activities in a warehouse effectively and efficiently, organisations use a Warehouse Management System (WMS). The WMS makes it easier to control what exactly is stored in the warehouse and where the items are stored (Connolly, 2008). In addition, the WMS performs more in-depth processes effectively with the least number of errors (Frazelle, 2001). To achieve more effective operational activities, increase productivity in the supply chain and drive competitive improvement, warehouses are being (re-) designed and automated to reduce the processing time and costs (Harmon, 1993).

Time and cost are not the only essential factors which influence the effectiveness and efficiency of processes in a warehouse. European Agency for Safety and Health at Work (2005) identifies noise at the workplace as a factor which causes disturbance of speech communication and work-related stress. Industrial equipment in the warehouse is known as the source of noise which results in poor communication using speech (Sound Proof Cow Inc., 2016). In addition, hands-full and eyes-busy operations handling in a warehouse are known as other factors reducing the effectiveness and efficiency of warehouse management and the operation manual tasks within the warehouse (MWPVL, 2016).

Wearable sensory devices are used as extensions to the regular warehouse clothing in order to enable the staff to perform operations hands-free and eyes-free. This has improved the interaction and usability of WMSs considerably, and has also decreased the amount of time one operation takes. Voice-based systems use powerful hardware and artificial speech recognition techniques which enable a user to interact with the WMS by using verbal communication, even in noisy environments (Voicepicking, 2015). Smart-Glasses are hands-free head-mounted devices that in addition to transmitting and understanding voice signals, allow users to transmit a video via a peripheral interface as well (Mann, 1997).

Other sensory technologies can be added to future warehouse clothing as well. Motion, orientation and location sensors measure the movement of an object. Brain-Computer Interface (BCI) is able to read brain signals with an Electroencephalogram (EEG) and uses various artificial intelligence algorithms to translate the biomedical signal (bio-signal)s into meaningful and useful data (Vidal, 1973). Muscle-Computer Interface (MCI) reads bio-signals from potential muscular activities with surface Electromyography (EMG) electrodes attached to the skin and translates them into data (Wand and Schultz, 2011). Using a variety of sensors can provide inexpensive favourable solutions to industries to improve Human-Computer Interaction (HCI) in a warehouse.

1.2 Existing Problems

Technologies such as Stock-to-Operators that bring materials or containers to warehouse personnel (Section 3.3.4) can facilitate operations in a warehouse as efficiently and effectively as possible, independent of noise. Such systems are very costly and are not commonly used. In addition, the lack of ability to handle the variety of items on pick lines reduces the popularity of these systems (De Koster, Le-Doc and Roodbergen, 2007). Therefore, in recent years, industry has focussed its attention on semi-automated management of warehouse operations by using sensory technologies such as voice-based systems (Section 3.6.5) and Head-Up Display (HUD – Section 3.6.6) when compared with other available methods such as using barcoding systems (Section 3.5.1.1) or RF scanning systems (Section 3.6.2).

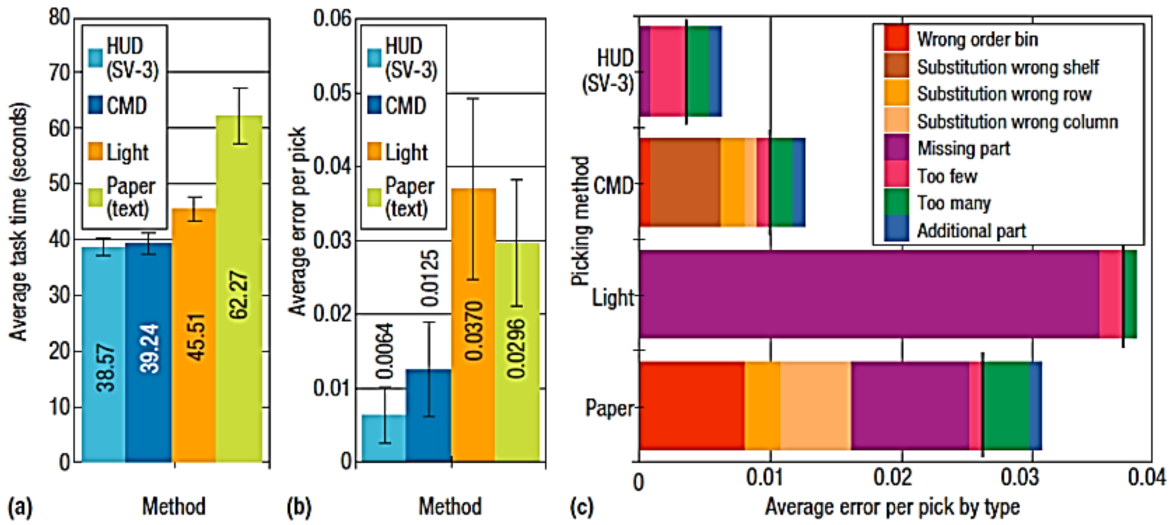

Figure 1-1: Comparing various automation technologies in warehouse order-picking. (a) Average task time, (b) average error per pick, and (c) average error per pick by type (Guo, et al., 2015).

Guo, Wu, Shen, Starner, et al. (2015) in an experiment, have compared the speed and number of occurring errors between different warehouse order-picking techniques including the traditional paper-based technique (Section 3.6.1), pick by light (Section 3.6.3), Cart-Mounted Display (Section 3.6.4) and pick by HUD (Section 3.6.6). Figure 1-1 shows the results of the experiment which indicates using HUD is the fastest method (Figure 1-1-a) with less errors (Figure 1-1-b) in a warehouse order-picking process. The HUD system adopts the Augmented Reality (AR) technique which uses Smart-Glasses (Section 5.2.3).

In general, the errors include substitution and picking-part errors (Figure 1-1-c). As an extension to the achieved results by Guo, et al. (2015), this research study places these errors into two different categories. First, the substitution errors that by using HUD and lightening methods have prevented their occurrence, as is presented in Figure 1-1-c, and second, picking parts errors that the user may cause them to occur while performing a task. Most errors that occur during the picking process can be a result of unintentional action slips (Section 4.7.2). Current WMSs that are using HUD and lightening methods have minimised the number of human errors that may be a result of memory lapse or mistakes.

A problem with using available Smart-Glasses on the market is that they cannot receive voice signals from a user in noisy environments accurately. Factors which may generate noise include, the industrial environment of a warehouse, transportation vehicles that travel inside the warehouse and industrial air conditioners installed in the warehouse building (Peterson, 2014; Strautins, 2014), as well as some warehouse equipment (Section 3.3.4).

The noise problem can be solved by combining the voice-based systems with the HUD. This combination considerably increases the costs of installation and results in reducing the favourability of the solution by the industry. In addition, Weaver, Baumann, Starner, Iben, et al. (2010), Guo, et al. (2015) and Herter (2010) have introduced voice-based systems indicating that they are slower than other systems as the user must provide inputs verbally and the system must process the command in order to recognise it. Using voice-based systems can also result in inaccuracy in data entry.

Consequently, the main research problem can be defined as:

> *The current sensory technologies used in a noisy warehouse environment create interaction problems with Warehouse Management Systems*.

1.3 Thesis Statement

This research aims to improve the current frameworks that use sensory technologies such as Smart-Glasses and voice-based systems to interact with a WMS in order to handle the daily operations in a warehouse. Thus, to address the problem statement, the following thesis statement is expressed:

> *A sensory technology, can be implemented and evaluated to improve the possible interaction with a Warehouse Management System.*

1.4 Research Questions

This study tries to investigate finding a solution for the problem mentioned in Section 1.2. The following research questions are posed in order to give a direction to the study.

Main Research Question

How can using a sensory technology improve the possible interaction with a WMS in a warehouse environment?

Secondary Research Questions

RQ1**:** What are the latest automation technologies used for warehouse management?

RQ2**:** What human factors are involved while performing daily operations in a warehouse?

RQ3**:** What are the latest sensory technologies which can improve the Human-Computer Interaction within the problem domain?

RQ4: How can a sensory solution improve the current interaction techniques?

RQ5**:** How effective and efficient is the selected sensory solution?

1.5 Research Objectives

This research will be conducted to acquire necessary information and knowledge which are required to evaluate a new solution using a sensory technology while a worker performs an operation in a warehouse environment. Therefore, the following primary and secondary objectives are set:

Main Research Objective

To evaluate a selected sensory technology that could improve the interaction with a Warehouse Management System.

The following additional research objectives are set to complement the main research objective.

Secondary Research Objectives

RO1**:** Identify the latest automation technologies used in warehouse management.

RO2**:** Identify human factors involved in performing daily operations in a warehouse.

RO3**:** Investigate available sensory technologies enabling human interaction with computer applications.

RO4**:** Select a sensory solution for improving interaction with a Warehouse Management System.

RO5**:** Evaluate the effectiveness and efficiency of the offered solution.

1.6 Scope and Limitations

Organisations are still performing operations relating to the moving and handling of materials manually utilising a number of workers. To transform an entirely manual system to a semi-automated system, the organisation must meet the minimum industrial standards and IT infrastructure (Booyens, 2014). Improving the manual process can be done by using robots, an Automated Guided Vehicle (AGV) and automatic storage and retrieval machines (Section 3.3.4). This research study focuses on solving the problem in semi-automated warehouses that are still using manual workers using HUD systems in performing daily activities.

Two existing problems in interaction with a WMS were discussed in Section 1.2. The first problem occurred while providing inputs to the WMS when the both hands of the user are busy (Section 4.9.1), in a noisy warehouse environment and the second problem caused by action slips (Section 4.7.2), while performing daily operations. The WMS provides the necessary information to the user using an HUD and on the other hand receives inputs via voice commands. These two methods are known as the most effective and efficient solutions on the market at the moment (Guo, et al., 2015).

Theoretically, this research study investigates the different sensory technologies, human factors and methods that lead designers to try and address both these problems. In addition, other technologies that can improve the way a WMS presents information and provides feedback to its user are discussed and identified. The research focuses only on solving the problem in input provision while selecting and evaluating the solution.

The literature introduces a variety of techniques which a designer can apply to design and develop a system. Adopting the most appropriate technique requires a considerable amount of time spent on the investigation of each technique separately. Therefore, because of the limited time of the study, it does not guarantee offering the most efficient and effective solution, but tries to offer knowledge-based artefacts which with a high probability fill existing gaps within the design.

1.7 Layout of Dissertation

The outline of the chapters of this research study is briefly explained in the list below. Figure 1-2 also depicts a view of the dissertation's layout.

Chapter 1 – Introduction

Chapter 1 provides a background of the problem domain and the application domain in which this research will be conducted. In addition, this chapter discusses and identifies the research questions and objectives of this study.

Chapter 2 – Research Design

In order to gain necessary knowledge about conducting a successful research, Chapter 2 presents the research methodology which the study follows. This chapter also justifies the appropriateness of the selected methodology by describing different layers of the study.

Chapter 3 – Warehouse Management and Automation Technologies

This chapter identifies warehouses and warehouse management as the application domain in which the problems occur. In addition, it identifies and discusses the latest automation techniques and equipment which currently are used in fully-automated and semi-automated warehouses. Chapter 3 explains how WMSs can be applied to warehouse management by investigating various functionalities which the latest WMSs on the market have offered to their customers. This chapter focuses mainly on introducing popular automatic communication and identification techniques and equipment used by different WMSs.

Chapter 4 – Human Factors Involved in the Interaction with Warehouse Management Systems

Chapter 4 identifies some human factors and behaviours that are involved when a user interacts with a WMS and performs a daily task in a warehouse environment. This chapter investigates human factors including human vision, hearing, verbal and sensory systems. It also discusses some human behaviours such as attention and physiological movement which enable a human to interact and perform operations in a warehouse environment.

Chapter 5 – Sensory Technologies for Human-Computer Interaction

Chapter 5 discusses the latest sensory technologies on the market (or in development) that can facilitate interaction with computer systems. This chapter categorises interaction techniques into visual, verbal, auditory, gesture and biological interaction. Additionally, it discusses how each technique enables a user to receive feedback or provide input.

Chapter 6 – Design and Evaluation of the Solution

Chapter 6 focuses mainly on the selection, and evaluations of actual IT-based artefact, as well as, the design of appropriate experimentation which aims at evaluating the performance and efficiency of the artefact. It provides details of all the steps involved in the design and development as well as the procedures involved in the experimentation.

Chapter 7 – Conclusions and Future Research

Chapter 7 presents the main deliverables of this study which are categorised into IT-based and knowledge-based artefacts. This chapter highlights the strengths and limitations that exist within the artefact. It also offers theoretical solutions to the design of artefacts as well as improving the offered solution. Chapter 7 presents new future research for conducting research opportunities in the future.

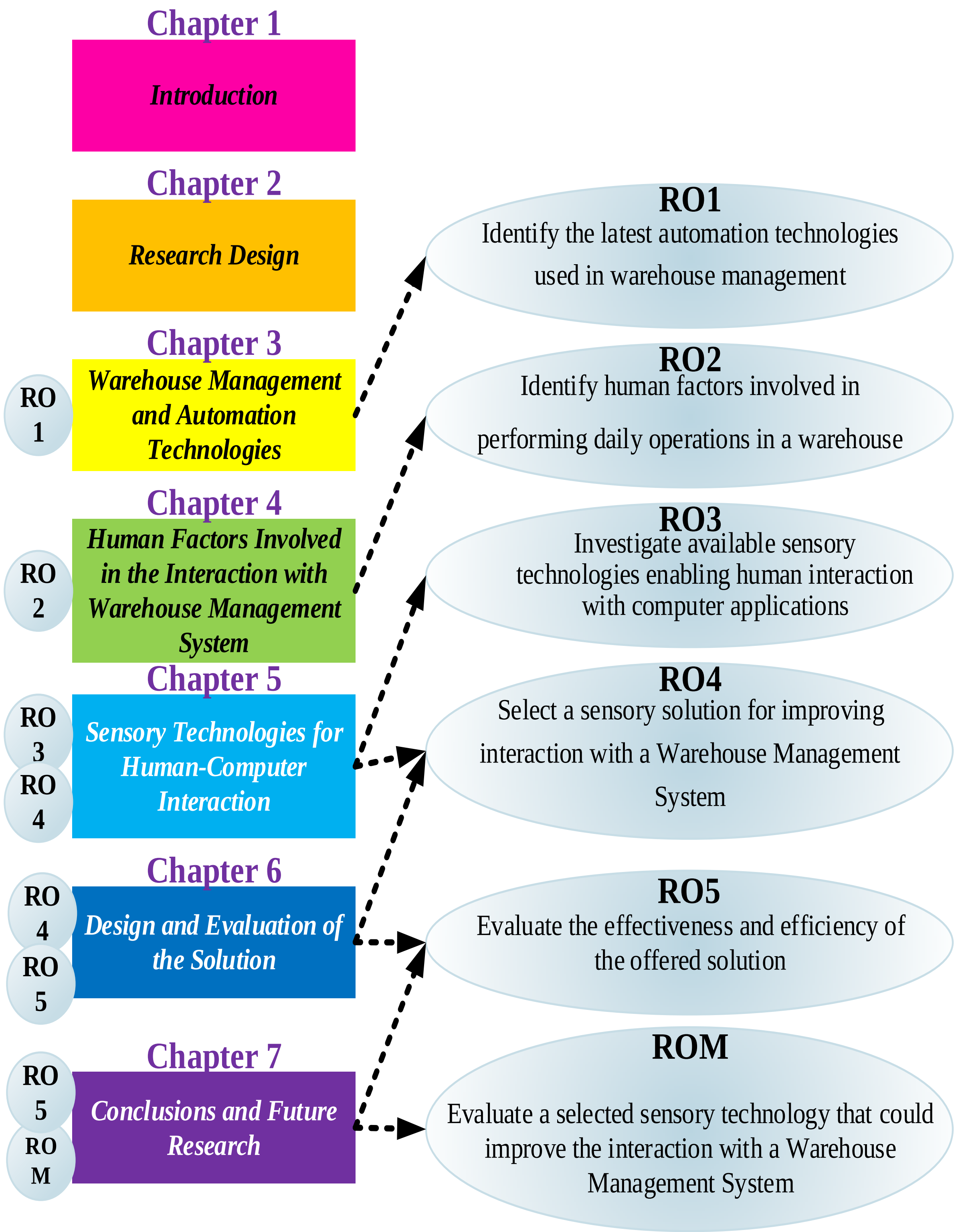

Figure 1-2: Structural view of the dissertation.

Chapter 2. Research Design

Objective(s) of Chapter

1. *To gain the necessary knowledge that can guide design science research.*
2. *Designing the research study.*
3. *Selecting an appropriate research methodology.*
4. *Adopting the methodology.*
5. *Introducing the deliverables of the study.*

Structural Overview of the Chapter

Chapter 1: Introduction

Chapter 2: Research Design

2.1 Introduction
2.2 Layers of Research Design
  2.2.1 Research Philosophy
  2.2.2 Research Approach
  2.2.3 Research Strategy
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2.7 Ethics
2.8 Summary

Chapter 3: Warehouse Management and Automation Technologies

Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems

Chapter 5: Sensory Technologies for Human-Computer Interaction

Chapter 6: Design and Evaluation of the Solution

Chapter 7: Conclusions and Future Research

2.1 Introduction

Zaheer (2015) identifies curiosity as the construction brick of the knowledge that has led humanity to wondering, noticing and eventually learning. Being curious aids a human to understand the world better (Hacker, 2013). Science is known as the human exertion to understand the real world and how the real world works. It can be done by observation of physical phenomena, and/or by experimentation that tries to simulate natural processes under measured conditions (Wilson, 2014).

Kuhn (1970) has defined research as an organised investigation to understand, explain, forecast and control the phenomena. Eames (2015) has defined design as *a plan for arranging elements in such a way as best to accomplish a particular purpose*. Therefore, the term research design can be identified as necessary elements and processes which must be considered in order to understand a particular subject of the research study.

All research studies begin with assumptions about how problems are solved in the real world and how we can recognise the solutions (Trochim, 2006). In the previous chapter the problem domain and the problem (Section 1.2) itself were identified and described. Therefore, in order to solve the main problem, research questions (Section 1.4) were identified as well as research objectives (Section 1.5).

A research methodology aims to give a systematic structure to the research study. This chapter, in order to formulate the research and guarantee its successful completion, discusses the different layers of the research design in Section 2.2 and identifies a suitable research methodology for the research in Sections 2.3, 2.4 and 2.5. In addition, this chapter explains how the selected methodology provides structure to the knowledge-based and technology-based artefacts (Section 2.6) that are presented in this research study. Section 2.7 explains ethical issues arising from this research study.

2.2 Layers of Research Design

Figure 2-1 depicts the different layers of research design known as the Research Onion that was introduced by Saunders, Lewis and Thornhill (2012). Bryman (2012) introduced the Research Onion as a useful analogy which can help a researcher to select a correct methodology in various contexts since it is adaptable to almost any type of research methodology. Basically, the Research Onion includes a sequential hierarchy of layers that the researcher has to peel off one by one to reach the lower layer and eventually the core. The initial layer determines the philosophy of research with the aim of indicating the nature of research study. In the second layer, the researcher determines an approach for the study. This approach would clarify the necessary procedures involved in the research design, starting from assumptions to detailed methods of data collection, analysis and at the end interpretation and evaluation of the research achievements. In the third layer, the researcher must select a strategy and implement it in the research study. Finally, the last two layers of the Research Onion consider the timeline and data collection methods.

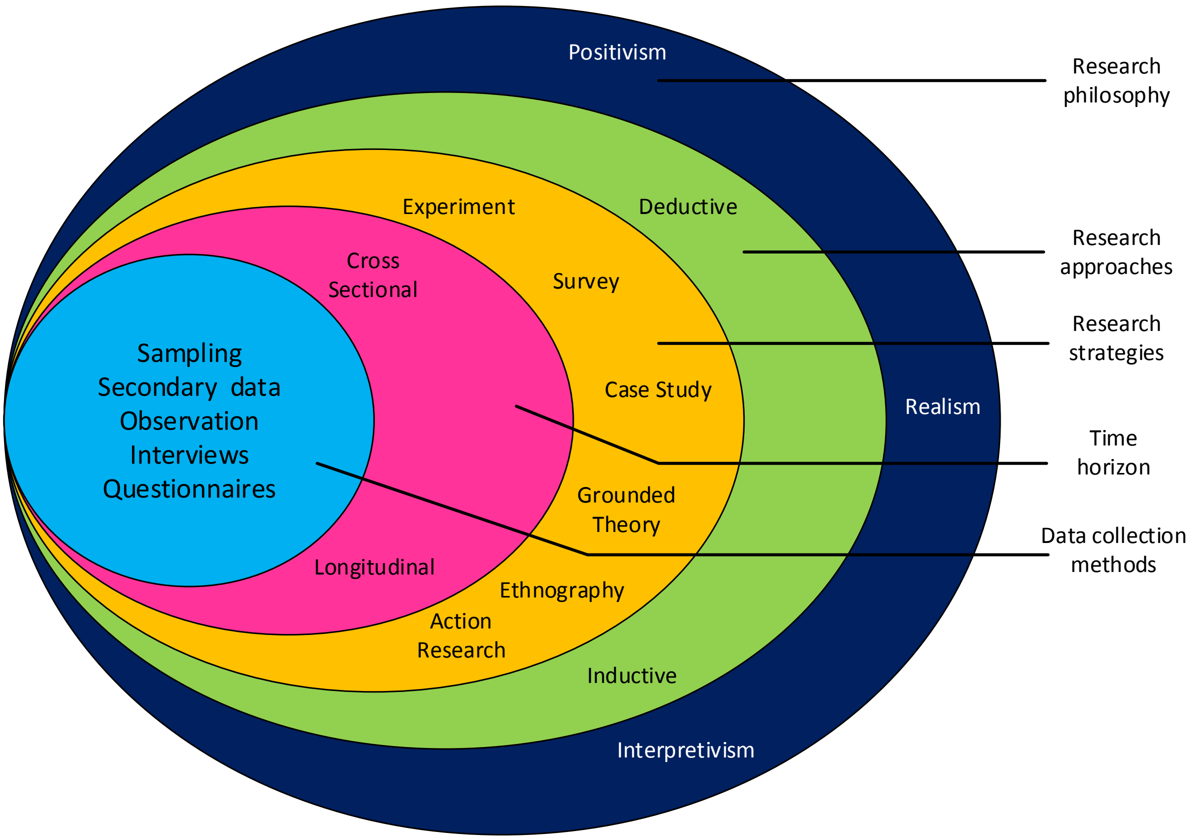


Figure 2-1: The Research Onion (Saunders, et al., 2012).

2.2.1 Research Philosophy

As it is defined in Oxford Dictionary (2015) the literal meaning of the term philosophy is love of wisdom and wisdom means the quality of having experience, knowledge, and good judgement. Therefore, apart from the aims of a research study, research philosophy can be defined as clarification of the research context and the nature of the knowledge domain that a research can be conducted in (Saunders, et al., 2012). The first layer of the Research Onion includes three main theories namely: positivism, realism and interpretivism that are briefly discussed next.

Positivism

Positivism is a school of thought that relies on specific scientific proof obtained from experimentation and measurement. Positivism tries to disclose the factual nature of how reality operates. It sees both the social and natural sciences as a product of verification and interpretation of data that can only be gained by observation via human sensory experiences (Mertens, 2015).

Positivism involves five significant principles which are listed below (Mastin, 2008):

1. The logic of research is similar to both social and natural sciences;
2. The aim of research is to explain and predict, and therefore to discover the required and adequate circumstances of any phenomenon in order to create knowledge;
3. Research must use an Inductive Approach (Section 2.2.2) in order to construct statements which can be evaluated via experimentation;
4. Science is not similar to personal opinion, and research should not be instructed by common sense; and
5. The judgement of science should be dependent upon logic and independent of any standards.

Realism

The school of thought, Realism, believes that reality is real, intelligible and absolutely independent of human beliefs (Phillips, 1987). In addition, it believes that all human beliefs and ideals in the current state are only an estimation of reality and new discoveries would bring us closer to understanding the features of reality. Realism also describes how a human reacts towards situations that may occur in an imperfect, real environment situation (Christensen and Johnson, 2014). In general, realism based research aims to generalise theories by analysing empirical findings (Sobh and Perry, 2006).

Interpretivism

Interpretivist research is a form of social science research that focuses on how a human interprets and understands experiences and the environment by which it is surrounded. The purpose of research based on interpretivism is to understand the social reality of individuals, groups and cultures by means of qualitative analysis (Major and Savin-Baden, 2012). *Interpretive researchers assume that access to reality (given or socially constructed) is only through social constructions such as language, consciousness, shared meanings, and instruments* (Myers, 2013, p. 38).

2.2.2 Research Approach

The Research Approach aims at planning the necessary procedures for research. It extends procedures from defining research questions to detailed methods of data collection, analysis, and interpretation. A research study can be conducted by two approaches: (1) Inductive, and (2) Deductive. The main difference between Deductive and Inductive Approaches is that the Deductive Approach aims at testing theory whereas the Inductive Approach is concerned with the creation of new theory emerging from data and the placement of theories, hypotheses and observations (Creswell, 2013). Also, as depicted in Figure 2-1, Saunders, et al. (2012) categorised the research approach layer into Inductive and Deductive approaches. Figure 2-2 depicts the instruction of both Inductive and Deductive approaches.

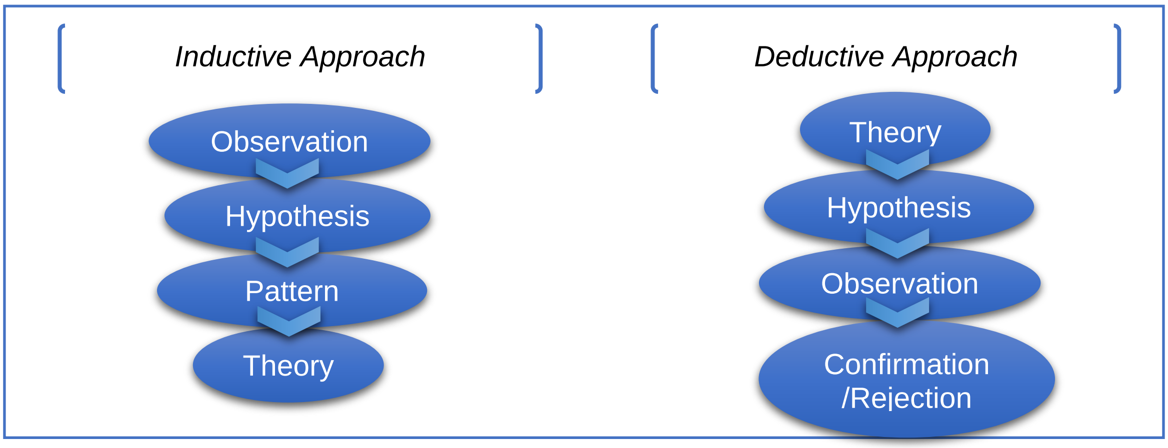


Figure 2-2: Research approach categorisation (Trochim, 2006).

The Deductive Approach extracts hypotheses from general theories and to achieve specific results, it conducts experimentation on various prospects of the hypotheses (Bradford, 2015). A research study in this category gathers and analyses quantitative data. Deductive research discovers a result from the interpretation of data that are collected during observation and experimentation. Data in the Deductive Approach can be analysed by statistical methods. The result of quantitative research is a structured report that includes introduction, literature studies, theories, methods, results and discussions (Creswell, 2013).

Unlike the Deductive Approach, the Inductive Approach progresses from the particular to the general (Bryman and Bell, 2011). In this approach, the research starts with an observation and then creates patterns from collected data (Beiske, 2007). In addition, in the Inductive Approach, there is no instruction that informs the data collection and research at the beginning. Therefore, the focus of study can only be formed just after the data collection (Flick, 2011). Inductive research tries to discover and realise social- and human-based meanings by collecting and analysing qualitative data (Creswell, 2013).

2.2.3 Research Strategy

A research strategy aims to give direction to efforts engaged during the study. The research strategy enables the researcher to conduct the research study methodically and this can be done through planning, executing and evaluating the study (Walliman, 2011). Selecting an appropriate research strategy is a crucial decision that can achieve particular research objectives. The researcher is able to select a research strategy depending on the goals and characteristics of the research (Saunders, et al., 2012). As was depicted in Figure 2-1, inside the third layer of the Research Onion, there is a number of research strategies by which the research can be conducted. These are listed and described below:

Action Research

Action Research covers studies that mostly have a practical approach to a specific problem and it involves examining practices. Originally, *Action Research could be divided into two processes. First, the diagnostic stage that includes studying the social state of the research as well as formulating theories related to the research domain. In the second stage the effects of the experiment and resulting changes would be introduced* (Hevner and Chatterjee, 2010, p. 27). Action research is most often used in community-based studies, co-operative enquiries, action science and action learning (Koshy, Koshy and Waterman, 2011).

Experimental Research

Experimental Research is a sophisticated research strategy that involves observing phenomena under measurable situations (Srinagesh, 2011). It always tries to compare the outcomes of an experiment with desirable results (Saunders, et al., 2012). Basically, during Experimental Research, the researcher observes the effects of external elements on internal elements where the external elements are manipulated through intermediations (Srinagesh, 2011). Generally, Experimental Research is used in some fields of sciences such as sociology, psychology, chemistry, biology, medicine and suchlike (Blakstad, 2008).

Case Study

A Case Study in research investigates and assesses a special unit with the aim of establishing its key features and of drawing generalisations from the research (Bryman, 2012). It can explore an insight into the specific nature of any example. Case Study research is used in social science, psychology, anthropology and ecology (Shuttleworth, 2008).

Grounded Theory

A Grounded Theory enables a researcher to expand theories which offer explanations concerning an issue in a specific population within practical domains. Additionally, it clarifies how an issue can be resolved (Scott, 2009). Grounded Theory is accepted as a qualitative research methodology to derive patterns from data which are requirements of the research study. Most often, Grounded Theory is conducted to understand human and social issues (Khan, 2014).

Survey

A Survey-based research study tends to be used in quantitative research. It involves sampling a representative proportion of the population (Bryman and Bell, 2011). It is known as a useful and economical method that enables research to extract knowledge about how a population thinks and feels. Survey-based research enables the researcher to assess views and changes within the problem domain. The data can be generated by questions and answers. The researcher concludes the results of research by analysing this data (Check and Schutt, 2011).

Ethnography

Ethnographic research involves close and particular observation of a target population, examining its cultural interaction and exploring a variety of meaning-giving cultures (Bryman and Bell, 2011). In order to extract a research result, an *Ethnographic research study relies on techniques such as observation, video* *diaries, photographs, contextual interviews and analysis of artefacts (for example devices, tools or paper-based forms that might be used as a part of the population's daily activities)* (Gov.uk, 2015).

2.2.4 Time Horizons

The Business Dictionary defines the time horizon as an *estimated length of time for a plan, program, or project to be completed, an endeavour to succeed, an investment to yield returns, an obligation to become due, a right to mature and suchlike* (Business Dictionary, 2015). The time horizon is the last layer of the Research Onion before the core. It is categorised into cross-sectional and longitudinal time horizons.

The cross-sectional time horizon is used for a research study which tries to answer questions or address a particular phenomenon at a single point in time. A research study in this category often studies a subjective population. Psychological, sociological and educational research are mostly included in this category (Saunders, et al., 2012).

A research study which has to collect data frequently over a protracted timespan to evaluate and compare the results of changes over the time would manage its timing based on a method called a longitudinal time horizon (Goddard and Melville, 2004). The longitudinal time horizon has benefits for studying changes and developments within a system (Saunders, et al., 2012).

2.2.5 Data Collection and Analysis Methods

As was mentioned before, the aim of conducting a research study is also to understand social or physical phenomena. In order to gain this understanding, during the research study, the researcher collects, analyses and presents data which can answer questions whose answers are not directly understandable and observable. Data collection is known as *the process of gathering and measuring information on variables of interest, in an established, systematic fashion that enables stated research question hypotheses to be answered, and outcomes to be evaluated* (Wikipedia, 2015a).

A proper and systematic data collection and analysis, not only increases the accuracy and quality of how a researcher can answer the research questions, it can also assist to improve the validity of the research study. Therefore, *it is important that the researcher selects appropriate data collection instruments and assigns precise* *instructions for the research study in order to decrease the probability of error occurrence* (Wikipedia, 2015a).

As was discussed in Section 2.2.2, any research study can follow an Inductive or Deductive Approach. A study can also use a mixed approach. Depending on the proposed approach, the research can be conducted by three different methods: (1) qualitative, (2) quantitative, and (3) mixed approaches that collect both qualitative and quantitative data (Creswell, 2013).

The University of Leicester (2015), in an online research-design tutorial, described qualitative data collection methods as those involving direct interaction with individuals on a one-to-one basis or by direct interaction with individuals in a group setting. In addition, it categorised qualitative data collection into four main methods including individual interviews, focus groups, observation, and action research.

The University of Wisconsin Eau Claire (2015) in another online research-design tutorial described quantitative research as concerned with testing the hypotheses derived from theory and/or being able to estimate the size of a phenomenon of interest. In addition, it categorised the quantitative data collection into four main methods including experimentation, observation, the use of available data coming from management information systems, and by utilising surveys.

2.3 Design Science Research Methodology

Information System (IS) applications are employed in the daily operations of an organisation in order to offer solutions effectively and efficiently for existing problems within the information processing phases. Zmud (1997) instructs IS researchers to develop and communicate *knowledge concerning both the management of Information Technology (IT) and the use of IT for managerial and organisational purposes* (Zmud, 1997, pp. xxi–xxii). Acquiring such knowledge includes two complementary but different paradigms, Design Science and Behavioural Science (Hevner, March, Park and Ram, 2004).

The Behavioural Science paradigm has its roots in research methods in natural science and tries to define theories. In order to increase the effectiveness and efficiency of an organisation, this paradigm uses theories that try to explain the behaviour of people and organisations and the analysis, design, implementation, management, and the use of IS. This can influence the selection of the IS development methodology and designing functionalities and the user interface of an IS (Hevner, et al., 2004).

The Design Science paradigm is closely related to information systems research since it addresses the role of an IT artefact in IS research (Weber, 1997). It has its roots in engineering and in the sciences of artificial systems (Simon, 1996). In order to involve IS in solving a problem effectively and efficiently, this paradigm tries to expand ideas, practical abilities, and the final products and services of an organisation (Denning, 1997).

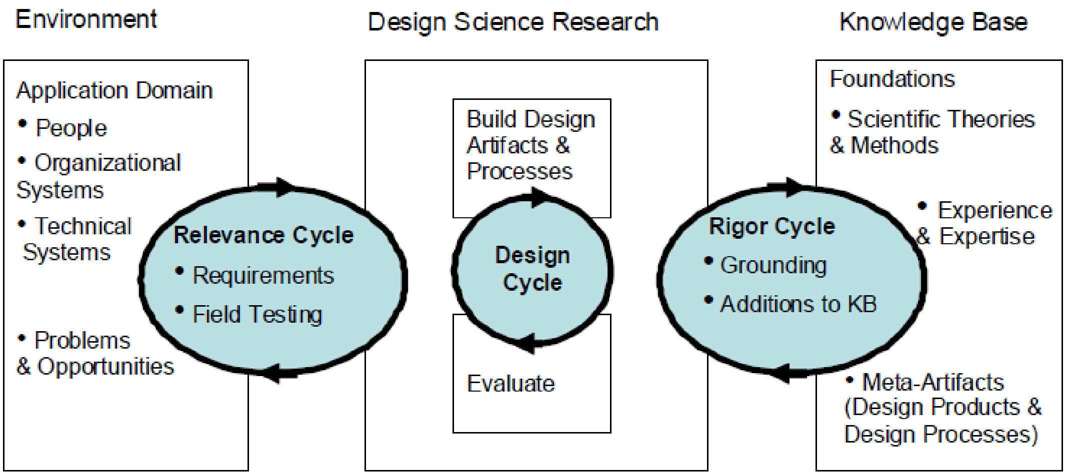


Figure 2-3: Design science research methodology cycles (Hevner, 2007).

As is depicted in Figure 2-3, Hevner, et al. (2004) present the DSR methodology as a conceptual framework by focusing on three different essential research cycles. Basically, the figure tries to facilitate understanding, executing, and evaluating IS research study by combining both Behavioural Science and Design Science paradigms.

2.3.1 Relevance Cycle

Basically an application domain consists of users (people, organisational systems and technical systems) who are involved in the daily activities of the organisation and are supposed to interact with the IS. The DSR has the purpose of identifying existing problems and opportunities in different environments within the organisation. This cycle ties the appropriate environment of the research to other activities in Design Science. Essential iterations in this cycle would be determined after the measurement of how the IT-based solution improves the environment (Hevner, 2007).

2.3.2 Rigor Cycle

To guarantee how innovative the research is, the Rigor Cycle provides past artefacts and processes them within the application domain by running a comparison between them (Hevner, et al., 2004). In addition, this cycle leads researchers to gather more appropriate methods and theories that facilitate the development and evaluation of IT-based artefacts (Hevner, 2007).

2.3.3 Design Cycle

Hevner (2007) introduces the Design Cycle as the heart of a DSR study. It basically consists of designing, developing, evaluating and using feedback to refine the design of an artefact. Iterations of these processes must be balanced and planned. Processes in a cycle must be supported by grounded theories and knowledge.

2.3.4 Guidelines for Design Science

As listed below, Hevner, et al. (2004) have introduced seven guidelines which facilitate understanding the processes of defining the problem and designing the solution.

Guideline 1: Design as an Artefact

Design Science research tries to solve organisational problems by defining a purposeful IT-based artefact. A purposeful IT-based artefact must be effective, implementable and applicable in the specific domain. The artefact can be formed as a model, prototype, construction, or a method and must have a practical use. In Section 2.6 the artefacts that are offered within this research study will be determined.

Guideline 2: Problem Relevance

Design and development of IT-based solutions require an appropriate knowledge of technology. The main aim of IS research study is to acquire and understand such knowledge. Behavioural Science expands this aim by stating theories that can explain and predict phenomena that occur within the problem domain, as well as, what factors influence implementing the artefact in the business environment.

Guideline 3: Design Evaluation

In order to assure the quality and efficacy of an artefact, the artefact needs to be evaluated rigorously. The evaluation is determined by the requirements that must be gathered from the business environment. The business environment includes the IT infrastructures which were developed and are still being developed by new IT artefacts. Therefore, evaluation must also include the influences of implementation of new artefacts on the business environment.

Guideline 4: Research Contributions

An effective DSR requires providing one or more contributions of the evaluation of a design artefact, design theory statement and/or design evaluation. The artefact must use innovative IT-based solutions to solve unsolved problems. Design theories can be stated with the contribution of the three main cycles within DSR. Measurable metrics and evaluation techniques can form this contribution in DSR.

Guideline 5: Research Rigor

DSR depends on the use of rigorous methods in the development and evaluation of artefacts. The applicability and generalisability of artefacts involved in the research design, can assess the rigor. Success is based on the selection of appropriate methods for the development or construction of theories or artefacts.

Guideline 6: Design as a Search Process

Design Science is an iterative process which tries to discover the most effective solution to a problem. Briefly, iteration can be divided into two main steps. First generating design alternatives and secondly, to test the alternatives against requirements and constraints. The iteration can cause refinement of design and construction of artefacts which produce a more desirable conclusion.

Guideline 7: Communication of Research

DSR must be presented both to technology-oriented and management-oriented audiences. Therefore, the DSR must determine the necessary organisational resources that have to be allocated to the implementation of artefacts. In addition, DSR must provide valuable knowledge about the effectiveness of applying the artefacts within a specific context in the business environment.

2.4 Experimental Research Methodology

DSR instructs a research study to design and develop IT-based and knowledge-based artefacts which may assist in solving the mentioned problem within the problem domain. In order to recognise the positive and negative effects of the implementation of an offered solution upon the main problem, this study will require the comparison of the solutions it offers with a desirable solution. DSR does not allow the study to conduct such a comparison, therefore, the study needs to apply Experimental Research methodology as well.

During Experimental Research, researchers manipulate and control experimental and non-experimental variables to realise the underlying processes of a phenomenon. Generally, they use standardised procedures to change some variables under different conditions except experimental variables. This can assist them to recognise the effects of a specific modification of an independent variable on different dependent variables (Blakstad, 2008). Hereby, they can control and measure changes within an environment. This standardisation ensures validity while comparing the dependent variable of one experimental group to a control group (Ross and Morrison, 2004).

In an Experimental Research study, the independent variable is the element that the researcher manipulates and controls in order to reach a desirable outcome. Hypotheses of a study determine the degree of manipulation and also the independent variable. On the other hand, the dependent variable, will be changed because of the changes made to the independent variable. Mainly, the dependent variable is a variable that the research study tries to measure (Boundless, 2016).

Key (1997) introduces the steps involved in conducting Experimental Research as:

1. To identify and define the problem;
2. Formulate hypotheses and deduce their consequences;
3. Construct an experimental design that represents all the elements, conditions, and relations correlation of the consequences;
4. Conduct the experiment;
5. Compile raw data and reduce it to usable form; and
6. Apply an appropriate test of consequences.

Odle and Mayer (2009) as well as Boundless (2016) have described Experimental Research design following the similar procedures that Key (1997) introduced.

2.5 Methodology Motivation

As was described and discussed in Section 2.2, Saunders, et al. (2012) have split layers of research design into five different layers. This enables a researcher to describe design research study as peeling off the layers of a Research Onion and selecting an appropriate element in each layer. In each layer, a researcher can determine the approaches and methods which assist to select a methodology. As depicted in Figure 2-4, in order to design a research study with the aim of answering the questions mentioned in Section 1.4, the philosophy, approach, strategy and timeline of the research are highlighted.

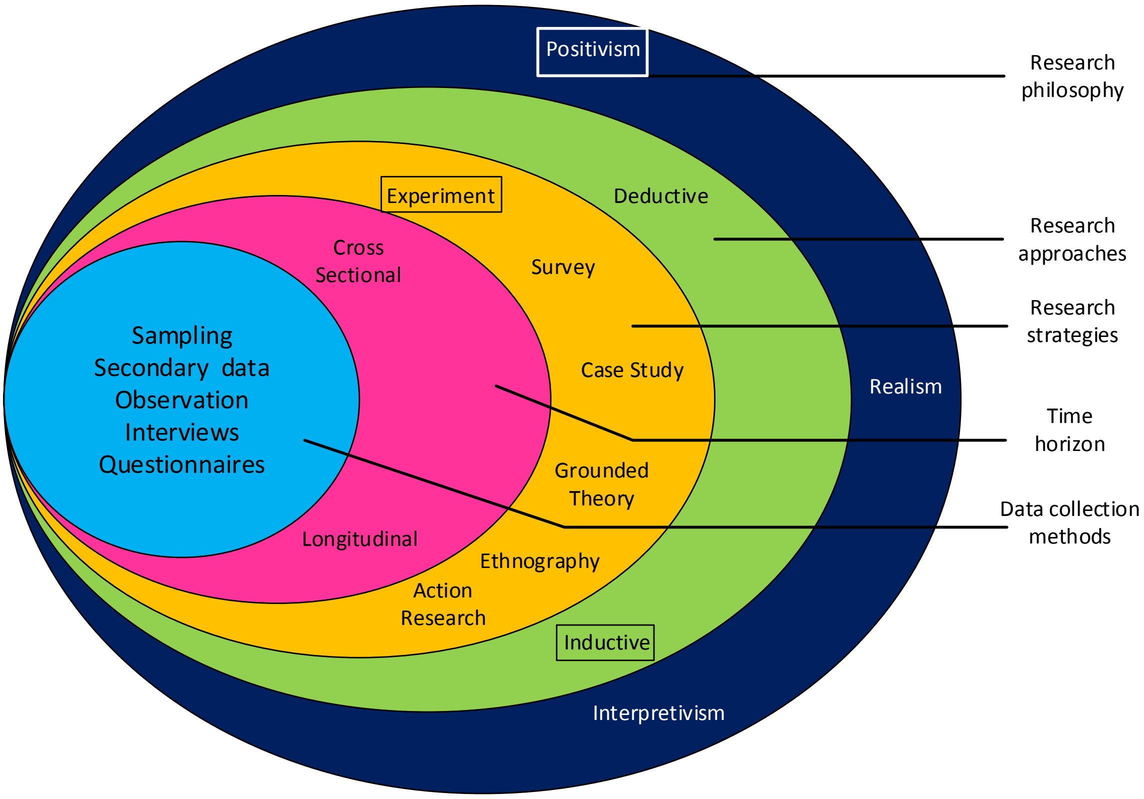


Figure 2-4: Peeling off the Research Onion (Saunders, et al., 2012).

The outer layer of the Research Onion expects a researcher, selecting the philosophy of a research study, to be concerned with the nature of study. As stated in Section 1.3, this research study tries to design and develop an IT-based artefact in order to observe its effects on improving the interaction with WMS in a noisy warehouse environment when both hands of the user are busy. This can be achieved by verifying and analysing data collected during observation and experimentation. This directly points to the Positivism Approach as was described in Section 2.2.1.

After peeling off the philosophy layer, the researcher selects an appropriate approach for the nature of the research study. As was discussed in Section 2.2.2, the researcher can make a choice between Inductive or Deductive approach. As an artefact, this research study tests theories that are stated by interpreting of data collected from observations and experimentations. Therefore, this study follows the Inductive Approach.

DSR sounds like a possible methodology to use in this research study to attain its objectives and offer a solution for the main problem. DSR formulates appropriate theories in order to diagnose the state of the research problem. In addition, it presents the effects of implementing the IT-based artefact and practical results of experimentations in the problem domain. To design an IT-based artefact, it is necessary to evaluate the artefact’s performance while faced with a variety of independent and dependent variables. Experimentation as the main process of an Experimental Research allows this research study to conduct this evaluation and observe the effectiveness and efficiency resulting from the implementation of the artefact upon the problem domain.

In the last two layers of the Research Onion, the researcher must schedule the timeline of the project and determine the data collection, data analysis and evaluation methods. Applied data collection and analysis methods in this study are identified and described in Chapter 6, Sections 6.8 and 6.9. Figure 2-5 presents a graphical structure of the research flow to present a better and easier understanding by following up the selected methodology throughout the structure of research.

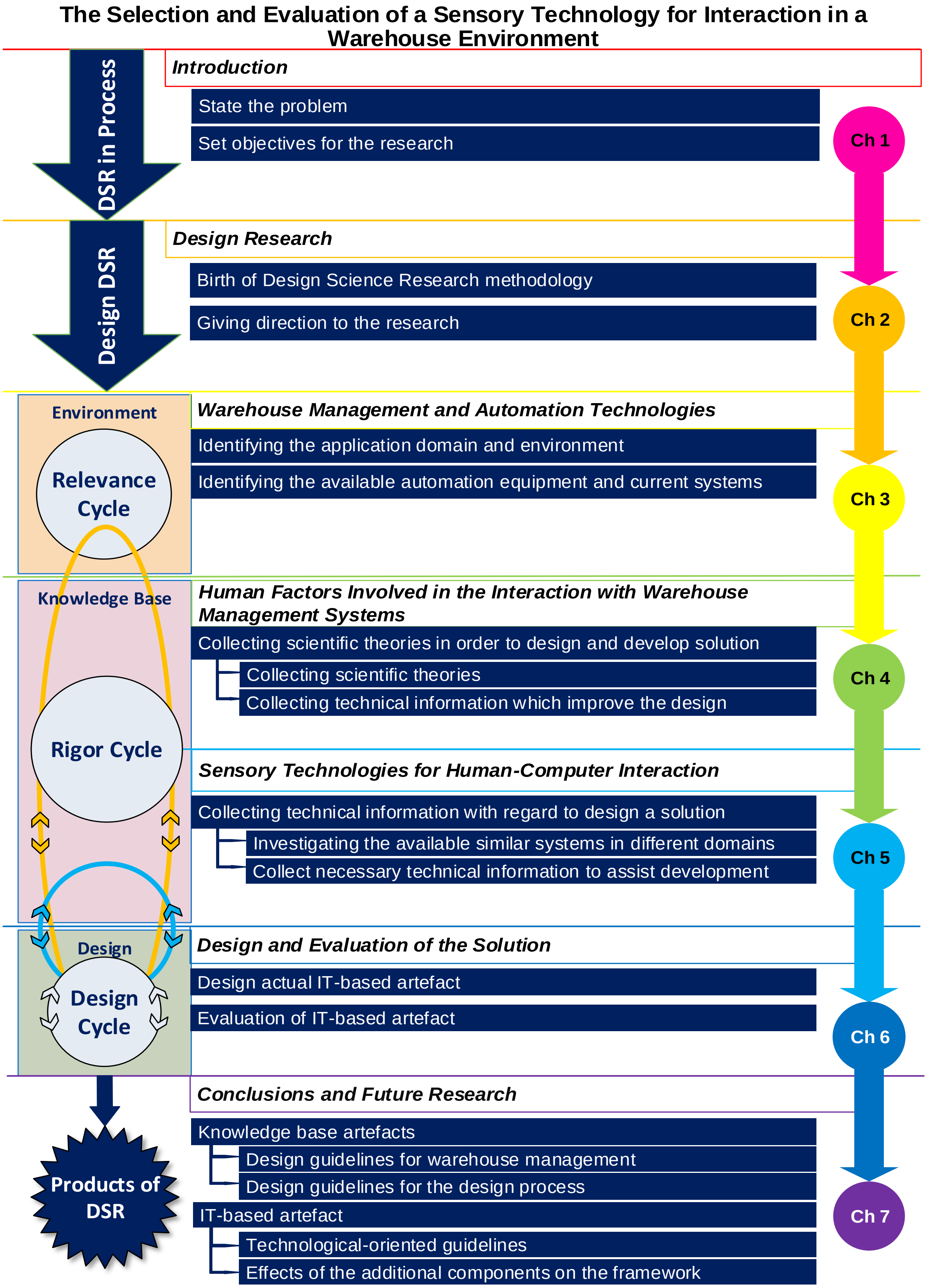


Figure 2-5: Research design flow diagram using Design Science Research.

2.6 Design Artefacts

In Figure 2-3, the Design Cycle of artefacts was depicted as the heart and main cycle of DSR and in Section 2.3.4, the importance of design, development and implementation of artefacts in a business environment were discussed. Two main artefacts will be introduced in this research study. The first is knowledge-based theories that are stated and explained in the literature study chapters in addition to theories that will be concluded at the end of this study, and the second is IT-based artefacts.

As Hevner, et al. (2004) mention, an artefact can be formed as a model, prototype, framework or product. A model in IS development can be defined as a conceptual presentation of the real world that is constructed by humans and helps better understanding of real world systems (Hacking, 1983). A prototype is an elementary working model of a computer system tested and built for presenting the purposes of DSR (Rouse, 2005). The aim of a framework is to structure something useful and this is defined as a layer of conceptual interrelations of some appropriate programs that do exist or should be developed and added to an existing framework (Rouse, 2015). A product can be defined as a tangible output produced at the end of DSR. The product can be a framework, model or prototype.

2.6.1 Agile Software Development

Agile software development is rather a popular philosophy of software development than a sequence of processes. Methods that follow agile philosophy, minimise risks by decreasing the time taken for software development but respect some specific principles, therefore agile development allows the release of products more frequently (Shore and Warden, 2008).

Shore and Warden (2008) have introduced twelve principles. From highest to lowest priority they include:

1. Customer satisfaction;
2. Flexible requirements at changes;
3. Frequent deliveries;
4. Collaboration between business people and the development team;
5. Keeping the team motivated;
6. Effective and efficient requirement gathering;
7. Measuring progress with a working prototype;
8. Sustainable collaboration between stakeholders;
9. Offering the highest quality design;

10. Maximising the amount of work;
11. The best design and architecture; and
12. Trying to upgrade behaviour of team effectively.

There are a number of methods that follow agile development, for instance Crystal Methods, Extreme Programming, Dynamic Systems Development Model, incremental prototyping and Scrum.

2.6.2 Extreme Programming Software Development Methodology

In order to minimise software development time, Extreme Programming Software Development (EPSD) methodology surpasses main software development processes including planning, designing, coding, testing and listening to feedbacks. Unlike traditional software development methodologies that have a linear point of view, EPSD enables a developer to iterate more efficiently than any other process at any time of development. It makes the development process quicker and more flexible.

In the EPSD's planning stage, in addition to the primary requests of customers, new functional or non-functional requirements of customers are also included. Planning a new change requires preparing for more costs and time. During the design stage, a designer must pay enough attention to design the system in such a way that the system can be extended in the future and also the new design must support new requirements. The coding stage is dependent on design. In addition to other processes, coding must follow a standard that allows the system be changed in the future with an acceptable amount of effort. The testing process occurs after the completion of each development stage. The produced prototype must be tested and evaluated continually that it satisfies all requirements. At the end, EPSD listens to feedbacks of all stakeholders in order to act upon them. Feedbacks are the main reason for an iteration and the changes in design (Nayab, 2011). Figure 2-6 depicts the processes involved in EPSD and iterations.

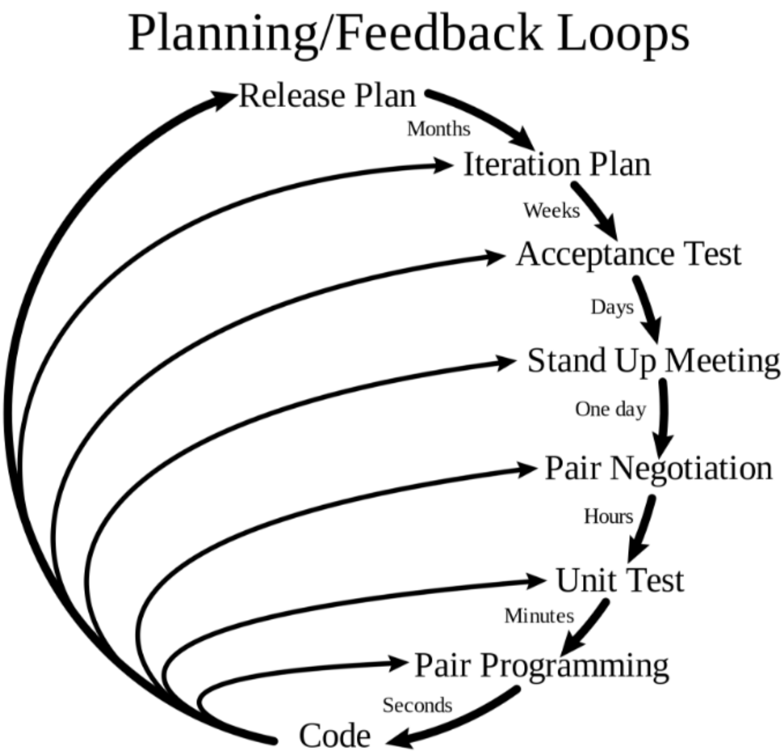


Figure 2-6: Planning and feedback at many levels and many frequencies in EPSD (Wikimedia, 2015).

2.6.3 Project Timing, Data Collection and Data Analysis

In the last two layers of the Research Onion, the researcher must schedule the timeline of the project and determine the data collection, data analysis and evaluation methods. Applied data collection and analysis methods in this study are identified and described in Chapter 6, Sections 6.8 and 6.9.

2.7 Ethics

Ethical norms in a research project are significant as they improve the aim of research and the values that are important to a cooperative work (Resnik, 2011). Trochim (2006) introduces a number of key principles that try to protect the rights of participants against Experimental Research. Key principles include considering consent, risk of harm, confidentiality, anonymity and the right of service. This research study will be carried out based on ethical issues and principles. User privacy may necessitate the submission of an ethics application to the Nelson Mandela Metropolitan University (NMMU) and is recorded at reference H16-SCI-CSS-002 (Appendix A).

2.8 Summary

In order to attain the objectives of this chapter, the contents followed an analogy introduced by Saunders, et al. (2012) who had likened the processes involved in research design with peeling off the layers of an onion from the surface to the core. The first layer determined the philosophy of the research project (Section 2.2.1). Three different views, expressing the research philosophy, were identified and discussed, namely: positivism, interpretivism and realism. The second layer considered different approaches to be used in a research (Section 2.2.2). Deductive and Inductive approaches were identified and briefly explained. The third layer stated the research strategy (Section 2.2.3) to be used in any kind of research study. The final two layers were concerned with the project timelines, data collection and analysis. Data collection and analysis processes were explained in Section 2.2.5 and timelines in Section 2.2.4.

Design Science Research (DSR) was identified (Section 2.3) and selected (Section 2.5) as the research methodology to guide this research project in the design and development of artefacts. Section 2.3 provided a theoretical background of DSR, wherein it was described as a cyclic process consisting of the relevance, design and rigor cycles. DSR's final outputs were introduced as, firstly, Behavioural Science artefacts that aimed at increasing the efficiency and effectiveness of IT/IS in an organisation, and secondly, Design Science artefacts that aimed at designing and developing the IT-based artefacts. Experimental Research methodology was also selected in Section 2.4 to assist the study by measuring the performance, effectiveness and efficiency of IT-based artefacts affected by different (non-) environmental factors.

The artefacts for which DSR instructed the research in design and delivery were discussed and designed in Section 2.6. In order to design and develop the IT-based artefact in this section, extreme programming was introduced and agile software development methodologies that guide this study to design and develop an IT-based solution.

Ethical considerations are involved in the DSR process and considerations are highlighted for each of the DSR cycles. Reference was also made to ethical clearance obtained from NMMU to conduct this research in Section 2.7.

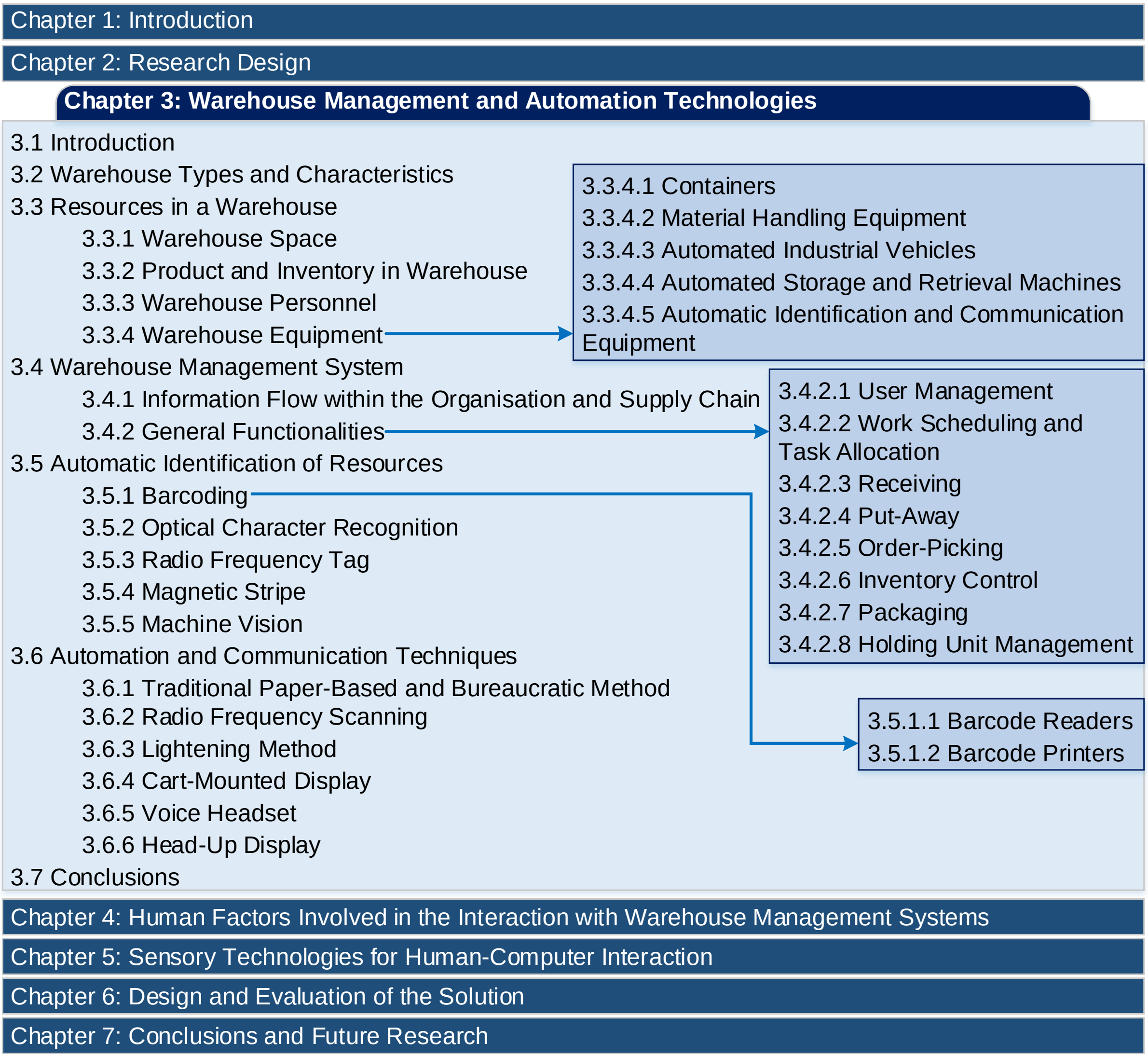
In the following chapter, warehouse management and automation technologies will be introduced.

Chapter 3. Warehouse Management and Automation Technologies

Objective(s) of Chapter

1. *Provide an introduction to warehousing and warehouse management.*
2. *Identify and discuss the main resources in a warehouse.*
3. *Introduce and describe Warehouse Management System (WMS) and its functionalities.*
4. *Identify and discuss the latest automation technologies used in a warehouse.*

Structural Overview of the Chapter



3.1 Introduction

A warehouse, as the Oxford Dictionary defines the word, is *a large building where raw materials or manufactured goods may be stored prior to their distribution for sale* or to be used within the different departments of an organisation (Oxford Dictionary, 2015). The early warehouses were established next to ports and railways with the aim of reducing the time taken for loading shipments and overseas transportations. A well-managed warehouse can simplify the movement of goods from the suppliers to the customers and in addition support the customers' demands and expectations (Tompkins and Smith, 1998). To achieve more effective and efficient operational activities, increase productivity in the supply chain, reduce the processing time/cost, and drive competitive improvement, modern warehouses are being (re-) designed to be as automated as possible (Harmon, 1993).

In the previous chapter, the Relevance Cycle was introduced as an essential cycle within the DSR with the aim of investigating the problem domain and the environment where a problem occurs (Section 2.3.1). An application domain could include people, organisational systems and technical systems. As a problem was defined in Section 1.2, the problem occurs when there is interaction with a Warehouse Management System (WMS) in a noisy warehouse environment when both hands of the user are busy.

In this chapter, in order to become familiar with the problem domain, at first, various warehouse types and characteristics will be introduced in Section 3.2. The resources a warehouse requires to survive and perform will be introduced and described in Section 3.3. These include space (Section 3.3.1), inventories (Section 3.3.2), personnel (Section 3.3.3) and equipment (Section 3.3.4). The mentioned resources will include those faced with the main problem addressed in this research, those that might cause or even prevent it. Then, Section 3.4 will introduce and discuss a WMS and the significance of equipping a warehouse with it. These significances will be noted by presenting the process of information flow between the WMS and other computerised systems inside the organisation and the supply chain. In Section 3.4.2 some operations which the selected popular WMSs support by providing appropriate functionalities, are described.

In Section 3.5, the latest technologies and techniques which are being used for automatically identifying a resource in the warehouse are introduced. This will be followed by introducing a number of popular methods which automate operations in the warehouse as are identified in Section 3.6. At the end, in Section 3.7, a discussion with the aim of addressing the results of the investigation into different automation technologies in warehouse management will be concluded.

3.2 Warehouse Types and Characteristics

Warehouses can be classified into a variety of types. Selecting the right type of warehouse can determine the facilities and the structure with which a warehouse must be equipped (Jenkins, 1990). For instance, a private warehouse is owned and managed by business enterprises which can afford to construct and manage a warehouse (KnowThis, 2015); A public warehouse is open for most organisations which cannot afford to have their own private warehouse. The organisations can lease the warehouse with short-term and temporary contracts (Chand, 2015); A temperature-controlled warehouse stores products that need special storage conditions. Some products such as foods, fruits, vegetables and medicines can be kept in this category of warehouse with the aim of holding these products for a longer time (Voortman, 2004); And an institutional warehouse keeps the items that may be used within an institution or organisation. For instance, a university keeps some stocks like paper, pen and printer cartridges in such a warehouse (Jenkins, 1990).

Each general type of a warehouse mentioned can have different characteristics as well. The characteristic of a warehouse would be determined by considering the type of products or services that an organisation related with it. For instance, a raw materials and component warehouse stores raw materials and parts which can be used in the production of a final product; A work-in-process warehouse stores partially completed products that can be used in the assembly or production stage; A finished-goods warehouse stores final products that are ready to be distributed and meet the demand of external consumers; A distribution warehouse stores accumulated and consolidated products from different source; and a fulfilment warehouse stores products that would fulfil small-size orders, such as supermarkets and retail stores provides (Frazelle, 2001).

Any warehouse is formed by a combination of different resources that determine the warehouse type and characteristics in addition to the way operations must be managed and operated in the warehouse. Therefore, in the next section

(Section 3.3), the focus of the study will be on warehouse resources which can be provided by any type and characteristic of warehouse.

3.3 Resources in a Warehouse

Zenieries (2014) has defined three significant warehousing resources which any warehouse has to deal with, namely: personnel, space and equipment. Emmett (2007) has introduced inventories in a warehouse as a precious resource as well. In the next sub-sections these resources will be introduced and described.

3.3.1 Warehouse Space

A warehouse building can be known as a space which can be purposefully divided into a number of different areas. The fragmentation of these areas regulates and improves the processes to be performed during the warehouse management. Basically, designing a layout for the space in a warehouse deals with determining the placement of different facilities and equipment as well as allocating an adequate space to each area which is supposed to be specified for a particular purpose. A well-designed layout in a warehouse minimises the time taken to move inventory and utilises the space allocation efficiently (Tompkins and Smith, 1998). The warehouse layout can be designed by considering and measuring the value of some variables. These variables can be defined as the number of storage locations, products, receiving and shipment points, the distance travelled and the time taken by a specific product to and from a receiving or shipment area (Hiregoudar, 2007).

Figure 3-1 presents an example of a general warehouse layout. The numbered areas present:

1. Storing/Picking area;
2. Replenishment area;
3. Door/Dock/Receiving area;
4. Shipment area;
5. Staging/Shipment area;
6. Staging area;
7. Warehousing department administration office;
8. Packaging area; and
9. Equipment holding area.

Figure 3-1: A warehouse layout example (Distribution Design, 2015).

3.3.2 Product and Inventory in Warehouse

Products are the most important element to determine a warehouse’s type and characteristics. A product is known as a tangible item that takes up space in the warehouse. The life cycle of the products in the warehouse starts with receiving each from a supplier and then, within a specific time (hours or may be years) it is shipped to meet a customer’s demand. In order to manage a warehouse efficiently, it is really important for the warehouse to have adequate information and understanding of products the warehouse wants to be stored in the warehouse (Francis, 2015). Products are the primary element that form the inventory of a warehouse. A product has specific features and properties that determine its maintenance, holding and movement methods while warehouse management is in progress.

On the other hand, an inventory is known as products, facilities, equipment (Section 3.3.4) and other goods that the warehouse holds. For inventory management of a product, in addition to its name and brand, the dimensions (height, width and length) are also important to know. Naturally, any object which has a mass and dimensions, has a weight as well. A product is made from different materials. Material and size determine a product’s units of measurement. Some products are measured by their weight and some by their quantity. A product also has a specific sale price and other factors which influence the storage costs. As listed below, to achieve an effective efficient inventory management, other information about a product can be added as well.

This list is extracted by investigating different Warehouse Management Systems, ERP systems and Inventory Management Systems (IQMS, 2015; Skuvault, 2015; SAP Help, 2015; and Syspro, 2015).

<u>Product Code</u>

A product code is a unique code (sometimes it is universal in the supply chain and global market) for the warehouse that identifies and contains the product. The product code facilitates the cost of management and tracing the product movement through the warehouse.

<u>Movement Type</u>

A product movement type relates to the amount of time a specific product stays in a warehouse. The most ordered products, which leave the warehouse more frequently, are rated as fast-moving and the less ordered products as slow-moving products. The movement type can be measured by the volume of entry within a specific period of time (for example a few seconds, a day, a week or maybe a year).

<u>Storage Type</u>

A product storage type deals with the specific holding regulations or methods by which products must be stored. For instance, ice-cream must be stored in -20° Celsius in freezers, headphones in boxes and a box containing 100 laptops is placed on a shelf. Storage type sometimes can indicate the level of safety and protection that a product must be held in as well.

<u>Unit Cost</u>

Unit cost defines the amount of currency that holding a product would cost the warehouse. Calculating this amount requires considering many factors (for instance movement costs, consumed energy costs, labour costs, holding costs and so on).

<u>Expiry Date</u>

Expiry data is *the end of the period for which the product is valid* (Oxford Dictionary, 2015). In other word, the expiry date indicates the level of the product's perishability.

Pick/Put-Away Method

Moving different products in a warehouse requires implementing different material storage methods by using different loading and unloading equipment to take items from an area and put them away in another area.

Shipment Method

Shipment method addresses the methods used for conveying the product in the supply chain between the suppliers, warehouse and customers. Some products can be transferred by courier or post while some need a fridge truck.

3.3.3 Warehouse Personnel

Personnel in an organisation fulfil several significant work activities. Managers and human resource experts have an important responsibility for organising and managing the personnel who must perform daily activities as effectively and efficiently as possible. Therefore, it is necessary to see and know the personnel as a precious asset to the organisation (Bianca, 2015). As listed below, there are various types of skilled personnel who can work in a warehousing department and in different areas of a warehouse (Tompkins and Smith, 1998).

1. A warehouse manager contributes to the development and reviewing of the warehouse’s policies, plans and strategies.
2. Safety experts assist managers with safety plans and perform necessary operations relative to actualising a plan.
3. Warehouse general workers are responsible for handling daily basic operations and inspections in the warehouse.
4. Supervisors can be known as team leaders who are responsible for monitoring and overseeing the warehouse practices and operations, as well as supervising all warehouse personnel and inventory movements inside the warehouse building.
5. Warehouse office assistants and administrators are responsible for assisting warehouse managers by controlling incoming/outgoing orders, monitoring and generating reports of all processes in the warehouse, allocating tasks to the personnel, notifying out-of-stock items, and managing communication with suppliers and customers.

Some warehouses still perform operations in a warehouse manually and employ a huge number of personnel to perform daily operations. This research study focuses its attention on designing a solution for operators who may have difficulty with interacting with a WMS because of objects being held and the noise which exists in a warehouse environment. For instance, supervisors and basic function workers would experience having this problem more frequently while performing daily activities than the other personnel.

3.3.4 Warehouse Equipment

Warehouse equipment plays a vital role in reducing the costs of warehouse management and has numerous benefits for the warehouse. For instance, the equipment can effectively and efficiently facilitate and improve the safe handling of materials, the tracing of products, responding to orders and monitoring the warehouse environment (Tompkins and Smith, 1998).

Tompkins, White, Bozer, Tanchoco, et al. (2007) categorise warehouse automation methods and equipment in the book *Facilities Planning*. Following this categorisation, this research study has extracted and summarised these categories to introduce and describe automation equipment, which is commonly being used in a warehouse and which has an impact on the main problem for which this research study is trying to provide a solution. The following sub-sections aim to introduce and investigate how equipment may influence automation.

3.3.4.1 Containers

A container facilitates the movement of products in a warehouse by making an appropriate unit load which holds materials and uses the space inside as efficiently as possible. The container is commonly known as a Holding Unit (HU). Selecting appropriate storage equipment depends on both the inventories in the warehouse and the daily operations that must be performed in it. For instance, Figure 3-2 presents a tote pan, pallet, skid box and carton box. A tote pan and carton box are fixed or portable HUs which hold items within its capacity. Pallets are generally used for holding items or HUs in a stable fashion by themselves. A pallet facilitates the movement of materials since it can be lifted using material transport equipment. A skid box is known as a heavy HU which frequently is used for unitising a wide variety of materials and cannot be transported manually.

Tote pan

Pallet

Skid box

Carton box

Figure 3-2: Four different types of containers (Warehouse Equipment Company, 2015).

3.3.4.2 Material Handling Equipment

Equipment in this category facilitates the movement, transportation and handling of materials throughout the warehouse building, between different areas. This equipment can potentially be a source of noise generation (Strautins, 2014). In this sub-section, conveyors and some industrial vehicle types are introduced.

A conveyor is mainly applied when materials have to move frequently between specific fixed points through a fixed path. Materials on a conveyor can be put in and taken out automatically (for instance by using robots) or manually (by using manpower). There is a wide variety of conveyors as are identified and described by Tompkins, et al. (2007). Figure 3-3 represents three different types of conveyors.

Chute conveyor (Warehouse Equipment Company, 2015).

Heavy and free conveyor (Dearborn Mid-West Company, 2015).

Heavy conveyor (Patton, 2007).

Figure 3-3: Three different types of conveyors.

An industrial vehicle is specifically to facilitate the handling of materials between different points in a warehouse building over long and variable distances. In the following subcategories, an industrial vehicle can be categorised into a walking, riding or automatic vehicle.

A Walking Industrial Vehicle is a popular and very commonly employed equipment with the purpose of automating a transportation and material handling over a short or long distance. The Walking Industrial Vehicle is simple to use and is favoured in industry since they have a low initial purchase cost and setup. Figure 3-4 presents only four examples of equipment in this category.

Hand cart | **Hand truck** | **Pallet jack** | **Walkie stacker**

Figure 3-4: Four different types of a walking industrial vehicle (Warehouse Equipment Company, 2015).

Riding Industrial Vehicles enable an industrial vehicle operator to drive and transport material loads along for long distances through the different areas in a warehouse. In comparison with Walking Industrial Vehicles, a Riding Industrial Vehicle allows carrying an additional weight and gives greater storage height. Figure 3-5 presents a pallet truck, counter-balanced lift truck and straddle carrier as a few examples of riding industrial vehicles. These vehicles can be selected and employed based on the material they will be handling.

Pallet Truck (Tcmforklifts, 2015). | **Counter-balanced lift truck (Hewitt Material Handling, 2015).** | **Straddle carrier (Greenport, 2015).**

Figure 3-5: Three examples of a riding industrial vehicle.

3.3.4.3 Automated Industrial Vehicles

Unlike the walking and riding industrial vehicles, an Automated Industrial Vehicle requires no human intervention. Instead, vehicles are automatically guided by electrified wires buried in the floor, magnetic tape lined along the floor, rails mounted in the ceiling, cameras mounted on the vehicle, wireless signals, or internal guidance systems (Tompkins, et al., 2007). Applying this category of vehicles in a warehouse can offer a proper solution for solving the main problem in a fully-automated warehouse.

Automated Guided Vehicle (AGV) is basically an auto-drive truck which is equipped with a steering motor. The AGV accesses its energy from storage batteries via an electric motor and it finds its path by means of an electromagnetic path-following system. The AGV is controlled by a microcomputer which allows it to communicate with a host computer through a proposed communication technique. The host computer, in addition to assigning a travel task to the AGV, monitors and manages all vehicles to prevent a collision between them. An AGV can be varied based on the technique by which it would be guided and how it would handle the materials. Figure 3-6 presents two different examples of an AGV.

As an example, an AGV can be controlled by a buried guide-wire in the floor which generates RF signals and sends them to antennae attached to the vehicle. To control the steering wheel and direct a correct path, wires change the strength of generated signals. Changing the frequency of signals in one guide-wire enables the AGV to switch from one guide-wire to another one. The AGV must be pre-instructed to understand changes of received frequencies.

Heavy Burden Carriers (Savant Automation, 2015).

Roto Smeets (Frog AGV Sytems, 2015).

Figure 3-6: Two examples of Automated Guided Vehicle.

As another example, as it is shown in Figure 3-7, a Kiva Robot lifts up and transports a shelf bin to an operator who is located at a fixed location. The Kiva Robot is equipped with a wireless system, location sensors and embedded processors that enable it to handle materials (Cohen, Uras and Koenig, 2015). In a large warehouse building, hundreds of robots may move in a moment. Figure 3-8 tries to present the handling of materials by Kiva Robots not only finding an accurate path but also preventing a possible collision is a considerable issue.

The Kiva Robot, in order to find the best path and prevent any conflict with other robots, applies Multi-Agent Path Finding algorithms. There are various high-quality Multi-Agent Path Finding algorithms such as M* and Conflict Based Search, but to have a low-cost solution, controlling robots in the warehouse is achievable and is managed by a combination of Enhanced Conflict Based Search and Highway Engineering algorithms. Cohen, et al. (2015) in the paper *Feasibility Study: Using Highways for Bounded-Suboptimal Multi-Agent Path Finding* have compared and experimented with a number of different algorithms to select the one that is most efficient and least expensive. Expanding and explaining the aim and architecture of these algorithms are beyond the scope of this research study.

Figure 3-7: Kiva robot (Parekh, 2015).

Figure 3-8: Shelf bins movement in the warehouse (Parekh, 2015).

Figure 3-9: Robotic retrieval (FANUC America Corporation, 2011).

Sorting transfer vehicles locate around a conveyor loop to load and unload any size of unit loads automatically at the destination and departure points. For instance, in Figure 3-9, a robot arm that can belong to this category is presented.

3.3.4.4 Automated Storage and Retrieval Machines

A machine belonging to this category basically aims to perform all warehousing operations by using a fully Automated Storage and Retrieval System (AS/RS). *A typical AS/RS operation involves the picking up a load at the front of the system, transporting the load to an empty location, depositing the load in the empty location, and returning empty to the input/output point* (Tompkins, et al., 2007, p. 243). Essentially, designing such a system requires complex engineering of all involved processes within the storage and retrieval as well as the involvement of other processes. This complexity is a result of the required accuracy that is demanded in designing such a system since all areas, locations, items and equipment must be placed on fixed points.

3.3.4.5 Automatic Identification and Communication Equipment

Conducting research on this category of warehouse equipment is the main focus of this research study, therefore, this study in Sections 3.5 and 3.6 will identify and describe the latest automation and identification equipment, techniques and technologies that are being employed in modern warehouses. Section 3.4 introduces a Warehouse Management System (WMS) as another type of automation equipment that facilitates managing, controlling and monitoring the information of all daily operations and resources in a warehouse.

3.4 Warehouse Management Systems

Organisations are constantly looking for various solutions that can help them to achieve their long-term objectives. Therefore, different businesses have tended to implement Enterprise Resource Planning (ERP) and integrated management systems to improve productivity efficiently and effectively. This also has improved the responsiveness of customers and suppliers (Ptak and Schragenheim, 2003). As a significant component of an ERP system, a Warehouse Management System (WMS) is an Information System which specifically controls all daily operations and activities in a warehouse, from the time that materials are received from the receiving area until the time they leave the warehouse from the shipping area. In addition, the WMS determines tasks that have to be performed by warehouse personnel as well as by some automation equipment (Van Den Berg, 2007). Some ERP systems have integrated WMSs but they do not support all the processes in a warehouse. This may be the reason why some organisations have installed a customised WMS separately from the ERP implementation with the aim of managing warehouse operations more effectively. Generally, the WMS tries to manage, control and perform all four main resources that were introduced in the previous section (Section 3.3). Tompkins and Smith (1998), Palacios (2014), Piasecki (2012) and Van Den Berg (2007) introduced the use of a WMS as one of the most significant factors for success in warehouse management and in controlling the supply chain.

Section 3.4.1 introduces the importance of using a WMS within an organisation and supply chain by explaining and discussing the dependency of other systems on the information the WMS provides. All warehousing operations that are being automated by using the WMS in a warehouse will be identified and described in Section 3.4.2.

3.4.1 Information Flow within the Organisation and Supply Chain

A WMS, as a necessary part of the supply chain in an organisation most often plays an intermediate role between disparate systems. The WMS receives and sends information to other components of an ERP system or ISs in the organisation. This is how the WMS performs all warehouse operations as efficiently and effectively as possible. An ERP system automates different activities across the different departments of an organisation with the aim of facilitating the flow of information between them (Velthoen, 2014). Conducting a research study on the information flow and its influences on the WMS's operations is beyond the scope of this research study, but it is important to know the value of this information and how it influences the performance of operations within the WMSs. As depicted in Figure 3-10, the WMS transfers information between different sub-systems of an ERP system.

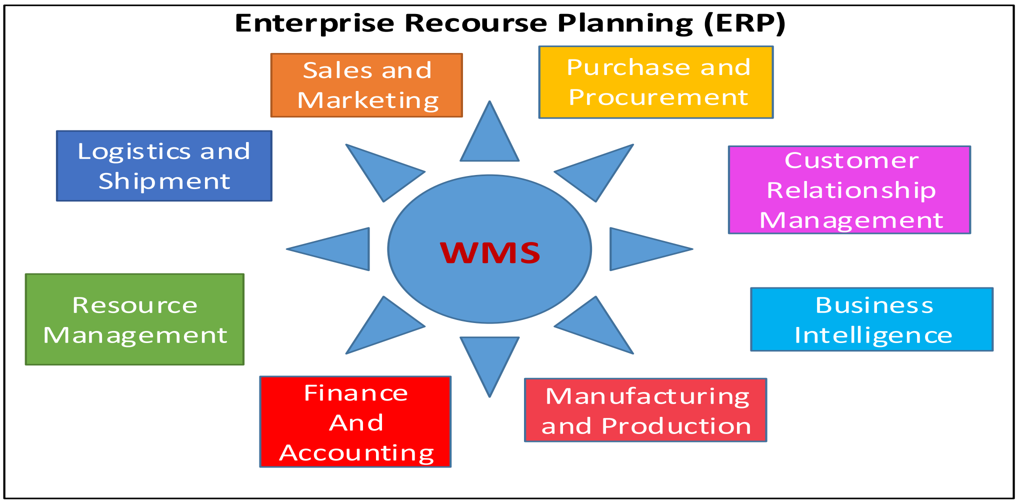


Figure 3-10: Warehouse Management System within the ERP.

A WMS may receive information about an incoming order from a Purchase and Procurement System as well as receiving information about an outgoing order from a Sales and Marketing System. In addition, a Logistic and Shipment System can provide essential information about a shipment (for instance date, time, method of delivery/shipment and shipment/receive gates) and the information of suppliers and customers can be served by a Customer Relationship Management System. A Finance and Accounting System will monitor and manage costs related to a warehouse and warehousing operations. It is possible that incoming and outgoing orders are repeatedly received from a Manufacturing and Production System (most often it happens in raw materials and finished goods warehouses). Personnel in a warehouse can be controlled and managed by a Resource Management System in the HR department. Finally, a Business Intelligence System can extract precious and useful knowledge by analysing the available information inside an ERP with the purpose of generating different, valuable reports.

By having a WMS-oriented point of view of the integration of different ERP/IS systems of a supplier, the main organisation and a customer, an improved definition of the supply chain can be extracted and defined. For instance, a mine ships extracted iron ore to a sheet iron producer, the sheet iron producer ships processed and manufactured iron sheets to a vehicle producer, the vehicle producer shapes them as a vehicle door, produces a vehicle by attaching the doors to other parts and ships the vehicle to a dealer on the market and at the end the final customer buys the vehicle from the dealer. In this supply chain cycle, raw materials are passed through a number of different warehouses of different organisations in order to convert raw materials into a final product. Therefore, when the final customer orders a vehicle, the information about this order would be handled by the dealer, vehicle producer (final products and raw materials), the sheet iron producer (final products and raw materials) and the iron mine's WMS.

This example highlights the significance of the WMS in the supply chain and how the dependency of processes between shipment and receiving pushes the organisations into a new level of integration. Involving the WMSs in this zone encourages the different warehouses in a supply chain to become smaller by being integrated with each other. This integration can improve and provide new distribution strategies, schedule work plans and ultimately increase the customer satisfaction (McCrea, 2014).

3.4.2 General Functionalities

The art of warehouse management is to operate a warehouse and to distribute products in it efficiently (Hompel and Schmidt, 2006). Briefly, the operations that are performed within a warehouse involve receiving products from a supplier, storing the products in the warehouse until they are required, picking the products when they are required and eventually shipping the ordered products to customers (Tompkins and Smith, 1998). In this section, the most popular functionalities of a WMS that support most warehouse management operations will be identified and described.

Not all available WMSs on the market support these operations, but in a configured WMS, these operations can be specifically added, modified or removed based on requirements of the warehouse and organisation. The following sub-sections explain scenarios which occur in different warehousing operations, and show potential information provided while they are in action. The WMS collects this important information by using different methods which will be introduced in Section 3.6. Information is gathered and extracted by investigating the different WMSs' abilities within their manual, help, catalogue or description (3PL Central, 2015; Bastian Solutions, 2015; Datascope, 2015; Datexcorp, 2015; JDA and Insync Solutions, 2015; Light Well Inc, 2015; Oracle, 2015; Rosmiman, 2015; SAP, 2015; Swisslog, 2015).

Shipment, manufacturing, space (sometimes known as layout or yard) and logistics management systems are often supported by WMSs, but expanding the discussion about these systems is beyond the scope of this research study.

3.4.2.1 User Management

Similar to other IS, a WMS, initially must be able to register the information of users and control their access and membership to the system. Restricting the users' access to different functionalities and information based on their needs increases the security of the information and simplifies the use of the system. Users' access levels are determined based on their level of responsibility in the warehousing department in addition to the tasks and operations that the user must frequently perform. For instance, a general worker should not have the ability to cancel an order since it is a managerial decision. And the general worker who is only responsible for picking-up orders must not have access to packaging functions. The policies in a warehouse and decision of warehouse managers or administrators determine the users' access level to suitable WMS functionalities and restrictions.

3.4.2.2 Work Scheduling and Task Allocation

Different daily operations in a warehouse sometimes are performed by manual workers and sometimes by automated machines, as was discussed in Section 3.3.3 (warehouse personnel) and Section 3.3.4 (warehouse equipment). Performing various operations in the warehouse is divided between personnel, one only receives items, one only packs an order and another one delivers the shipment to a customer (Kozenski, 2013).

As soon as an incoming/outgoing order is released, necessary operations to handle the order are initiated. However, it is not the only time an operation is initiated in a warehouse, other activities such as inventory control, generating a report for senior managers and other departments would also demand the initiation of an operation. The WMS must be capable of scheduling work in the warehouse by assigning appropriate tasks to appropriate personnel. The work scheduling and assignment of tasks can be performed by the warehouse office assistant, administrator or automatically by the WMS itself.

3.4.2.3 Receiving

Receiving initiates when materials are received by a warehouse for the first time as the result of a purchase order, Advanced Shipping Notification or blind receipt (when the quantity of ordered items is not clear) (Bastian Solutions, 2015). The items in an incoming order are always unloaded from a truck manually or automatically through receiving doors/docks as soon as they arrive at a warehouse. The types of truck, the quantity of the received items and the frequency of the receipt of the items determine the number of required doors/docks in a warehouse. Once items are unloaded, all of them have to be moved to a safe and suitable area, called a receiving area (Koumpourelou, 2008).

An ideal order-receiving process includes moving items to the most appropriate location with as little handling as possible. Selecting appropriate material handling equipment for the receiving process plays a vital role during the receiving process. Other processes involved in receiving, such as quality check, good labelling, initial count and late/missed delivery dates, all influence the outcome of the receiving process (PurpleStains, 2011).

After unloading an incoming order, it is important to count, code and label materials carefully and accurately. This can be performed by receiving personnel or by automatic receiving equipment. The accuracy of the initial count influences the efficiency of inventory and warehouse management positively. While received items are being counted, they can be inspected for quality acceptance as well. Any damages, discrepancies and irregular conditions/qualities must be reported immediately (WERC, 2007b).

Incoming orders sometimes are received with the supplier’s specific packaging. If the received order’s packaging is not appropriate for storage in the warehouse, it must be unpacked and repacked appropriately, otherwise, the same package can be moved to the next area directly. After the receiving process, items that must be stored in the warehouse wait for the put-away process.

3.4.2.4 Put-Away

When items are ready in the receiving area, they must be stored in a correct location. Emmett (2007) advocates the put-away process is dependent on whether the warehouse uses fixed or random storage locations. A fixed location refers to a location which is received for a specific product constantly. A random location refers to a location which the WMS decides automatically or the user does it manually. Technically, the put-away process involves choosing a specific quantity of received items from the departure location (receiving or staging area) and then moving them along a specific path to the correct storage area using appropriate equipment.

3.4.2.5 Order-Picking

Order-picking is the process of picking and collecting the ordered items by using appropriate picking equipment before the shipment (Hompel and Schmidt, 2006) to respond to the customers' demand. In order to increase customer satisfaction, organisations try to provide the earliest possible shipment date since customers expect same-day delivery. This has resulted in more emphasis on reducing cycle time. A cycle time in a warehouse picking order is defined as the amount of time that an order entry takes to be shipped and delivered to the customer (Piasecki, 2011).

A released order can have various qualities and attributes that indicate information related to an order. An order, in general, can be divided into a header that contains general information of the order and a number of lines that are basically the quantity and number of ordered items (extracted from investigating the released invoices by Apple.com, Amazon.com and Ebay.com companies). An order header includes some information such as:

- An order number (unique for either the organisation or supply chain);
- Customer's details (including name, address, telephone number and so on);
- Delivery method (include courier, post, delivery by the gate and so on);
- Preferred packaging (which type of packaging the customer prefers to receive the ordered items in or which type of packaging is more appropriate to the order delivery);

- Invoice details;
- Order status (new order, under processing, shipped, cancelled, partially shipped and delivered);
- Released date; and
- Approved date.

Based on an organisation's expectations and needs other attributes can be added or removed as well.

An order line is basically the items that a customer has ordered. The order line can include the following attributes:

- Product name;
- Product code;
- Ordered quantity;
- Price;
- Discount;
- Weight;
- Dimensions;
- Handling method;
- Estimated shipping cost;
- Packaging method; and
- Amount of tax.

Once an order is released, the WMS automatically, or the warehouse office assistant and administrator manually, allocates items to each order line. Ordered quantities of ordered items are not always available in the warehouse and an ordered product is not always stored in only one location in the warehouse. Therefore, order lines can include other entities that may not be visible to the customer such as allocated quantity and available quantity (Gmiles, 2011). When products are allocated to order lines, the system assigns an order-picking task to an order-picker or automated retrieval vehicle inside the warehouse building (it can be an automatic work scheduling and task allocation process).

3.4.2.6 Inventory Control

In addition to the functionalities that are related to handling incoming/outgoing orders, there are other functionalities that a WMS can use to improve the warehouse and inventory management effectively and efficiently. These functionalities basically enable the warehouse management to find out and certify the location where all items are stored (Tradegecko, 2015). The most popular functionalities that perform the inventory control are identified and described briefly:

Trace a Holding Unit (HU)

This is the primary function of a WMS that returns the location of an HU. An HU can be a shelf, pallet, box, area, and even a building.

Trace a Product

This shows the storage location(s), where the specific product is stored. The returned location most often is a hierarchy of HUs. For instance, Building A, Area B, Shelf C, Floor D, Unit E, Box F.

Count

This function can be performed frequently to confirm the actual inventory in the warehouse with the one stored in the WMS database. In this operation personnel/automated vehicles are assigned to trace a product and count the available quantity of the product in the stored HU(s).

Split

This function splits a specific number of available items inside one HU into different HUs.

Combine

This is the process of combining contents of one HU with the contents of another HU. For example, picking an item from a box and putting it on a pallet or in a tote.

Consolidation

This function consolidates products in different HUs into a single HU. This can be used mostly to reduce the dispersion of products around the storage area.

Quality Check

This function can be performed frequently to generate a report about any damage, expiry, and irregular state of items in the warehouse.

Inventory History

This function presents a report of all events which a specific item has experienced in specific periods of time.

The mentioned functions can be used by other functionalities of the WMS as well. For example, while picking an order from an HU, the order-picker first splits items between the picking HU (for instance a box on a shelf) and the box on its trolley. Then, the order-picker combines the box with other contents in the destination HU (for instance other boxes or items on the pallet). Quality check and count functions can also be performed while picking an order to report any damage or mismatch with the inventory.

3.4.2.7 Packaging

When an order is picked or received, if items in it are not packed desirably, they must be moved to the packaging area first. In this area the picked/received order would be unpacked to be packed again with the desirable packaging method. This process is called repacking. The desirable packing in the receiving process depends on storage policies and storage HU types. While responding to an order the packing depends on the customer's demands. Appropriate packing efficiently improves space utilisation in the warehouse and in the shipping vehicle. An efficient process to pack/repack items can be determined by considering the weight, size, methods of transportation, maintenance method, the required packaging equipment and the material the items are made of (WERC, 2007a).

3.4.2.8 Holding Unit Management

In general, this functionality enables warehouse managers to have a hierarchical perspective of all HUs in the warehouse in addition to the history of their lifecycle. A hierarchy of HUs can be formed as a main land of the warehouse. The land may have different warehouse buildings constructed on it. Each building may have a number of areas inside and each area may consist of various storage areas or equipment. The storage areas can consist of different containers inside and each container may keep another container inside.

3.5 Automatic Identification of Resources

A major benefit for companies that have large warehousing environments is automation. Equipping a warehouse with the most appropriate automation technologies reduces the use of manpower; makes the flow of material more efficient; improves productivity; reduces safety risks; reduces building costs; reduces inventories; and saves more space (Booyens, 2014). WMSs can be differentiated from each other by required hardware. The use of unique identifiers is commonly being used in the field of warehouse management which intends to make the reading and tracking of all resources of the warehouse more efficient. The following sub-sections introduce the latest automatic identification and communication technologies and techniques that are currently being used in the modern WMSs.

3.5.1 Barcoding

A barcode is a piece of paper that stores a limited amount of data on its presentation space. It can be attached to an object and be scanned to present specific data. Barcodes can be one-dimensional or two-dimensional (Richards, 2014). The barcode has a specific printed pattern on it and different alphanumeric characters in different codes. The combination of dimension, pattern and the alphanumeric value differentiates barcodes from each other (Makebarcode, 2015).

To express this differentiation as well as bringing some examples out of all different barcodes introduced in the website of Makebarcode, (2015)[1], Figure 3-11 presents the barcode “Code 128” that can encode the digits 0 through 9, six symbols (‘ – ’, ‘ : ’, ‘ . ’, ‘ $ ’, ‘ / ’ and ‘ + ’), and the start/stop characters A, B, C, D, E, *, N, or T. The start/stop characters must be used in the similar pairs and may not appear elsewhere in the barcode. In comparison, Figure 3-12 presents the barcode “EAN-13” that is used globally to identify items universally. The symbol encodes 13 characters. The first two or three are a country code which identify the country in which the manufacturer is registered. The country code is followed by 9 or 10 data digits (depending on the length of the country code) and a single digit checksum.

Figure 3-11: Code 128.

Figure 3-12: EAN-13.

Figure 3-13: PDF-417.

Figure 3-14: QR Code.

Figure 3-13 presents the barcode “PDF-417” that can store up to about 1,800 printable ASCII characters or 1100 binary characters per symbol and Figure 3-14 presents “QR Code” (Quick Response Code) that can encode up to 2509 numeric or 1520 alphanumeric characters.

[1] http://www.makebarcode.com/

Both “Code 128” and “EAN-13” barcodes present data with a one-dimensional pattern where “PDF-417” and “QR Code” present data with a two-dimensional matrix code. Two-dimensional barcodes are more appropriate in applications where the data must travel with the labelled item. Expanding the discussion over the barcode design does not have influence on achieving the objectives of this study, therefore, this study next introduces technologies that have improved the applications of barcodes in various fields.

3.5.1.1 Barcode Readers

A barcode reader is a device with the ability of scanning and reading a barcode by a variety of scanner devices. The barcode reader device emits infrared light onto a barcode and reads the light’s reflection from the barcode. To satisfy different industries, and increase the application of barcode scanners, they are designed in a wide variety of models and shapes. Table 3-1 presents some popular types of a barcode scanner comparing them with each other (Tompkins, et al., 2007).

Table 3-1: A comparison of different barcode readers.

	Light Pen	*Hand-held Laser*	*Stationary*	*Omnidirectional*	*Gloves*
Range (cm)	Contact	153	153	254	153
Depth of field	Contact	61 (cm)	102 (cm)	77 – 153 (cm)	61
Scan rate (Scan/Second)	Manual	32 - 100	200 - 3450	1440 - 2400	32 - 100
Resolution (mm)	0.10-.19	0.10- .19	0.10- 1.01	0.10- 1.016	0.10- .19
Hands-free	✘	✘	✓	✓	✓
Figure	Figure 3-15	Figure 3-16	Figure 3-17	Figure 3-18	Figure 3-19

Figure 3-15: Light pen (Ute, 2015).

Figure 3-16: Hand-held laser scanner (Cplonline, 2015).

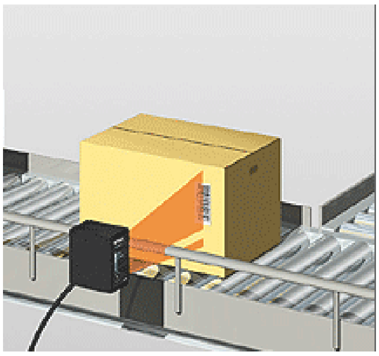


Figure 3-17: Stationary scanner (Keyence, 2015).

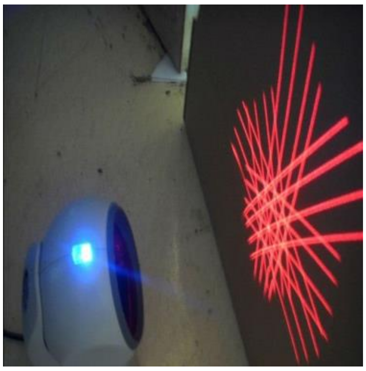


Figure 3-18: Omnidirectional scanner (Aliexpress, 2015).

Figure 3-19: Gloves scanner (Salestores, 2015).

3.5.1.2 Barcode Printers

A barcode printer enables the personnel in a warehouse to print barcodes on a sticker. The barcode printers use various printing technologies such as thermal transfer, laser and matrix printing. Available portable printers on the market enable the personnel to print a barcode to identify an item at any time anywhere in the warehouse.

3.5.2 Optical Character Recognition

An Optical Character Recognition system is a slower system than barcodes that uses hand-held scanners to read characters. Data in this method is printed on an item as a series of different characters and text. As it is shown in Figure 3-20 the scanner is able to read and recognise the printed text on items by having direct contact with it (Tompkins, et al., 2007).

Figure 3-20: Optical Character Recognition scanning system (Gadgetsgo, 2015).

Figure 3-21: Variety of RF tags (Controlelectric, 2015).

3.5.3 Radio Frequency Tag

A Radio Frequency (RF) tag stores dynamic data on a chip that is covered in a tag (Tompkins, et al., 2007). Tags can be read when they come within a range by means of an RF antenna inside the tag (Zeimpekis, Psarrou, Vlachos and Minis, 2008). RF tags uniquely identify different items they have been attached to. An RF tag is called active when it uses its own supplied power and it is called passive when it is powered by the electromagnetic energy transmitted from a reader. RF tags come in different shapes and dimensions as was shown in Figure 3-21 in above tried to depict them. The RF tag can be visible in the entire supply chain (Tompkins, et al., 2007).

3.5.4 Magnetic Stripe

A magnetic stripe is used for storing a large amount of data within its storage space. The most common example of the application of magnetic stripes is on the reverse of credit and bank cards. They can store editable dynamic data (Tompkins, et al., 2007).

3.5.5 Machine Vision

The Machine Vision system performs by taking a picture of various objects and sending it to a computer which interprets and recognises the picture. Generally, this technology relies on image recognition techniques. It is rated as a system with reasonable speed and accuracy, but it is only applicable to a limited number of environments (Tompkins, et al., 2007).

3.6 Automation and Communication Techniques

In general, equipment and methods belonging to this category are employed in warehouse management to facilitate communication with a WMS and collect data from activities and events. Technologies and methods that will be introduced are: traditional paper-based, RF/Barcode scanning, lightening method, cart-mounted display, voice headsets and Head-Up Display.

3.6.1 Traditional Paper-Based and Bureaucratic Method

In this method, the personnel are assigned their daily tasks that are written on paper. The printout contains a list of tasks that are divided into multiple steps and operations. The problem with this method is that the personnel may face difficulty with reading or understanding long product codes. Using this method forces personnel to perform each step in two different stages: first, reading and understanding details in the list and second, moving materials from one HU to another one. The personnel must carry the list with one hand so it reduces their ability to handle materials (Guo, et al., 2015).

3.6.2 Radio Frequency Scanning

An RF scanner is used for scanning RF tags and reading the data stored inside them. The data can be sent directly to a main computer via a wireless network, sent to another mobile computer via Bluetooth technology or be stored in the scanner natively. For the native storage of data, the device would be connected to a computer later and the data transferred into the WMS.

In comparison with a barcode scanner, an RF scanner is able to read several tags at the same time. This has provided an opportunity to warehouse managers to improve the efficiency, accuracy, speed and productivity of the warehouse. The application of this technology increases the hands-free performing operations in the warehouse. The RF scanners can be fixed (for example on conveyors and gates), hand-held (it is the same size and shape of portable barcode scanners that were depicted in Figure 3-16) or embedded (the scanner is embedded into a lift truck and/or gloves for example).

3.6.3 Lightening Method

In this method, as is depicted in Figure 3-22, a small display is attached to a storage area (in this case a shelf bin) in addition to some push buttons. This system is available for vertical carousels, mobile carts, mini-load AS/RS and vertical lift modules as well.

Figure 3-22: Lightening system (Fachanzeigen, 2010).

In the lightening system the worker walks through the lanes in the warehouse until he/she arrives at the destination. The system indicates the location(s) where the worker must perform a task there with a light illuminating the scene automatically. Digits on a display present the quantity that they must work with. This system is reported as a cost effective solution that increases the operations' speed, search time, documentation time and data collection accuracy (Guo, et al., 2015; Tompkins, et al., 2007). Embedded buttons enable the system to capture the data of worker's activity.

3.6.4 Cart-Mounted Display

Instead of attaching a display to each bin, this method uses a display mounted onto the carts (as is shown in Figure 3-23). Embedding a large screen to a cart has improved the interaction with WMS and has enabled the worker to explore more information on its large screen as will be introduced in Section 5.2.1.

Figure 3-23: Cart-mounted display (SpacePole, 2015).

3.6.5 Voice Headset

A voice headset uses synthesised voice communication and Voice Recognition technologies to establish a two-sided communication channel between WMS and the user. The system converts the data from the WMS into synthesised speech (as will be identified in Section 5.4) and the personnel's requests/responses into understandable data for the WMS using speech recognition techniques (as will be identified in Section 5.3).

Figure 3-24: Voice headset (Storact Log, 2015).

Figure 3-24 presents how the user wears the headset and places the earphone(s) on the ear(s) and the attached microphone opposite of mouth. The location and design of modern microphones and Voice Recognition software enable the interaction with the WMS even in a noisy hands-free and eyes-free area. The headset communicates with the main computer by radio frequency. Accuracy of this system has been estimated at 99.5% (Tompkins, et al., 2007). The technology behind a voice headset will be discussed in Section 5.3.

3.6.6 Head-Up Display

The use of the Head-Up Display (HUD) technique in recent years has attracted the attention of WMS designers and has encouraged them to adopt the Augmented Reality (AR) technique which uses Smart-Glasses (Figure 3-25) while performing a task through the WMS. Smart-Glasses is a computing device with a wearable optical head-mounted display (Dominguez, Keaton and Sayed, 2006). As is shown in Figure 3-26, Figure 3-27 and Figure 3-28 the application of augmented reality technology enables users to view the real world in addition to the extra information which the device provides and presents to them. In Figure 3-26, a path and information presentation on the Smart-Glasses environment is shown. In Figure 3-27, a confirmation box that requires a user’s response is presented. A problem with some of popular portable barcode scanners is that they need to be held by hand, but as is shown in Figure 3-28, Smart-Glasses scan a barcode as soon as it reaches the visual range of the glasses.

Figure 3-25: Smart-Glasses (Marks, 2015).

Figure 3-26: Path finding (Belatrix, 2015).

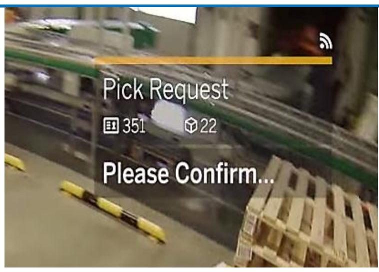


Figure 3-27: Confirmation box (Vuzix, 2015).

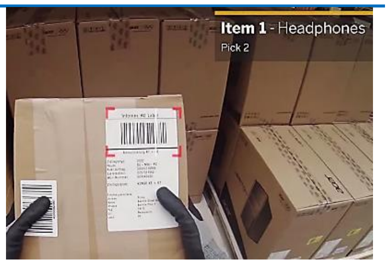


Figure 3-28: Barcode scanning (Vuzix, 2015).

3.7 Conclusions

This chapter attempted to describe warehouse management and the latest automation technologies pursuing two different purposes. Firstly, to identify the application domain that this research study has been conducted in. Secondly, to answer the first research question, *what are the latest automation technologies used for warehouse management?* (Section 1.4).

To pursue the first purpose, as was explained while defining the Relevance Cycle in DSR (Section 2.3.1), an application domain consists of users and the user in DSR was identified as the people, organisational systems and technical systems. An introduction to warehousing was provided by describing the different warehouse types and characteristics in Section 3.2. This would be specified for a warehouse by allocating the least required resources in a warehouse in Section 3.3. The purpose was to give a background of the environment where the main problem occurred when a user interacts with the WMS (Section 1.2) and to become familiar with various factors influencing the solution design process.

Different resources in a warehouse were introduced including the space (Section 3.3.1), inventories (Section 3.3.2), personnel (Section 3.3.3) and equipment as a valuable inventory in the warehouse (Section 3.3.4). Among all the described resources, a few types of personnel such as general workers and supervisors in the warehouse were identified as the people who might be potentially faced with the main problem more than other personnel. The warehouse space was briefly introduced and was not discussed in detail because it did not have a considerable impact on the objective of this research study. Unlike, handling and applying some inventories to performing a task by using a WMS was introduced as the potential element which causes the existing problems in the interaction with a WMS in Section 1.2.

Employing an Automated Storage and Retrieval System (AS/RS) within a warehouse was introduced as the most powerful and effective automation technique in Section 3.3.4.4 which reduces the probability of the main problem's occurrence in the interaction with a WMS. The performance of AS/RS can be best observed when the system is combined with an appropriate item-identification technique (Section 3.5). The AS/RS optimally integrates robotic arms with automatic conveyors to handle the flow of materials between different areas without the involving manpower. Equipping a warehouse with such a system is justified by the resulting economic benefits and the degree to which the system is able to handle all ranges of items in the warehouse.

In a warehouse, as was discussed in Section 3.3.4, while an item is being transported and handled, the specifications of the item (Sections 3.3.2 and 3.3.4), material handling equipment, and the method by which it is held in a warehouse (Section 3.4.4) determines the degree of the required essential amount of effort and manual involvement (Section 4.9.1). Other equipment introduced could also adjust this degree in the warehouse.

In Section 3.4, a Warehouse Management System (WMS) was introduced as a significant resource of a warehouse which improves the warehouse management process effectively and efficiently. The WMS collects, manages, controls and monitors necessary information of activities and events in the warehouse as accurately as possible to establish this improvement. Then, the significance of equipping a warehouse with the WMS within the organisation and the supply chain was introduced in Section 3.4.1. This was followed by discussing the various scenarios explaining a product flow from the time items are received at the warehouse to the time they leave the warehouse to satisfy a customer's need in

Section 3.5.2. The objective of discussing this scenario was to give a background of the minimum information that should be captured by the WMS when it automates the operation.

To pursue the second purpose, as the main research problem was stated in Section 1.2 (*The current sensory technologies used in a noisy warehouse environment create interaction problems with Warehouse Management Systems)*, the solution to be offered has to have a focus on sensory technologies and equipment in a warehouse which are used to communicate and interact with a WMS. Therefore, to continue, the methods and technologies used in the identification of items (Section 3.5) and communication with the WMS (Section 3.6) were introduced. While identifying techniques for the identification of items, a two-dimensional barcode was introduced which is more effective than a one-dimensional one since it holds more data. The use of RF tags is a faster and more effective technique when compared with barcoding.

Table 3-2: A comparison of automation techniques.

Methods	*Hands-Free*	*Speed*	*Eyes-Free*	*Performance in Noise*	*Accuracy*	*Automation Degree*
Bureaucratic	✘	Low	✘	✓	Low	Low
RF Scanning	✘	Medium	✘	✓	High	Medium
Barcoding	✘	Medium	✘	✓	High	Medium
Lightening	✘	Medium	✘	✓	Medium	Medium
Cart-Mounted Display	✘	Medium	✘	✓	Medium	Medium
Voice Headsets	✓	Low	✓	✓	Medium	Medium
HUD	✓	High	✓	✘	High	High

To focus on solving the main problem, in Section 3.6, the methods, as well as the technology being employed in each method, which can facilitate the performance of daily operations by using a WMS in a semi-automated warehouse were described. Table 3-2 below contains a summary and comparison of the key attributes of each method that is being employed in modern, semi-automated warehouse environments where the materials are handled manually (Section 4.9.1). Briefly, the rating of each method is determined based on how efficiently it performs in noise and enables hands-free and eyes-free (Section 5.2.3) interactions. In addition, the method's accuracy in collecting data is also considered.

The degree of automation can be defined as the evaluation of the general performance of a method when it is being faced with other key factors. As it can be observed in the table, employing the HUD in interaction and communication with a WMS is suggested as potentially the most efficient automation technique. This was the same as the result Guo, et al. (2015) had achieved during the comparison of a few techniques. This was headed in Section 1.2 when stating the main problem.

In the next chapter, the Relevance Cycle in DSR (Section 2.3.2) will be in action with the aim of gaining necessary knowledge for the design of a solution. Chapter 4 will introduce and discuss some human factors which are involved in performing a daily operation when using WMS in a warehouse environment. This can give background knowledge to help in the design and development of a solution using sensory technology. In Chapter 5, interaction techniques with a WMS and the requirements for designing a solution with a sensory technology will be presented.

Chapter 4. Human Factors Involved in the Interaction with Warehouse Management Systems

Objective(s) of Chapter

1. *Introducing human factors involved in the interaction with a WMS.*
2. *Introducing the human sensory, visual, hearing and speech production systems.*
3. *Discussing the association between human attention and the action of counting items.*
4. *Discussing the physical human movements involved in performing daily tasks in a warehouse including handling materials manually and speech production.*

Structural Overview of the Chapter

Chapter 1: Introduction
Chapter 2: Research Design
Chapter 3: Warehouse Management and Automation Technologies
Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems

4.1 Introduction
4.2 Human Sensors
    4.2.1 The Neuron
    4.2.2 Human Senses
    4.2.3 Sensory Receptor Cells
4.3 The Human Brain
    4.3.1 Areas of the Brain
    4.3.2 Neural Oscillation
    4.3.2 Different Brain Activity Patterns
4.4 Visual Perception
    4.4.1 The Human Eye
    4.4.2 Mediating Brain Areas
4.5 Speech Production
4.6 Auditory Perception
    4.6.1 The Human Ear
    4.6.2 Mediating Brain Areas
4.7 Attention
    4.7.1 Automaticity
    4.7.2 Action Slips
4.8 The Human Brain and Counting Action
4.9 Human Movement
    4.9.1 Manual Materials Handling
    4.9.2 Hands and Finger Gestures
    4.9.3 Speech Production
4.10 Conclusions

Chapter 5: Sensory Technologies for Human-Computer Interaction
Chapter 6: Design and Evaluation of the Solution
Chapter 7: Conclusions and Future Research

4.1 Introduction

Sense is *a faculty by which the body perceives an external stimulus. It is one of the faculties of sight, smell, hearing*, *taste, and touch* (Oxford Dictionary, 2015). To create a culture where humans and computers interact, humanity has been driven to increasing use sensory technologies. Sensors have facilitated communication between humans and computers and vice versa.

The study of human factors involves inspection of way human beings interact with any system (Kohn, Corrigan and Donaldson, 2000). The study into human factors can help to simplify the way a human performs different tasks. One obvious example of such an improvement can be the way that modern cars enable drivers to adjust their seats for comfort in comparison with cars produced twenty years ago. The evolution of this improvement is still continuing. This study is to investigate the employment of different sensors and how they could be used in a warehouse regarding the interaction with a WMS.

The latest technologies that are being used in interaction with a WMS as well as in daily operations in a warehouse were introduced and discussed in Chapter 3. The WMS receives some information from its user and responds to it to establish the interaction and communication. Inputs of the WMS can be text or voice and output can be a message on a screen or even a voice message. Therefore, it is obvious that a human, in order to interact with a WMS, needs to use visual, language production, auditory and body movement systems as well as the brain which is responsible for managing all behaviours and activities.

This chapter in order to answer the second research question *(What human factors are involved while performing daily operations in a warehouse?*), introduces all sensory systems (Section 4.2) that enable humans to recognise the incoming sensory information from the external environment. The human brain as the central processing unit of all human activities and behaviours as well as the way humans can measure its activities and performance (Section 4.3.2) will then be discussed in Section 4.3. The brain helps humans in concentrating on performing a task (Section 4.7) and gives us a perception of all different incoming information within the external world. The human visual perception (Section 4.4), speech production (Section 4.5) and auditory (Section 4.6) capabilities will be discussed as they are known as the basic necessities to establish any kind of interaction.

Human-based errors and how the human makes an error are discussed in Section 4.7.2. Most order-picking errors occur during counting items (Section 1.2), therefore this chapter takes a look at different ways a human counts given items in Section 4.8. Human movement factors relative to the daily operations in a warehouse (Section 4.9), including manual handling of materials (Section 4.9.1) and also speech production (Section 4.9.3) will be discussed. Final conclusions will be provided in Section 4.10.

4.2 Human Sensors

Senses are significantly related to the human awareness of real world and also its ability of a human to interact with the physical world. Principal to this awareness and ability of interaction are various sensory systems and the nerve cells that arbitrate their functioning. Together with the nervous system, these structures enable a human to receive various types of information about the environment and perform actions within it purposefully (Sickels, 1868). To explain this process, the following sub-sections describe the structure and functions of nerves, the types of senses as well as instances where senses interact.

4.2.1 The Neuron

Neurons are cells of the nervous system that generally are comprised of several basic components as are shown in Figure 4-1. Neurons differ in notable ways when compared to other cells. Dendrites are clusters of branch-like structures that are responsible for receiving information from other cells. Another structure peculiar to the neuron is the axon that can vary in length. Information travels through the neuron, starting from dendrites when the information is received, to the axon and it travels along the axons' length until it reaches the terminals at the end of the axon length. At the terminal the information can be transmitted to other neurons (Flagg, 2015).

The transmission between neurons is in the form of electrical impulses. An action potential or spike event happens when a neuron fires in order to communicate within a network of other neurons. The neuron basically discharges itself by opening and closing the $Sodium^{+}$ and $Potassium^{+}$ ion channels in the neuron membranes (Draper and Marshall, 2014).

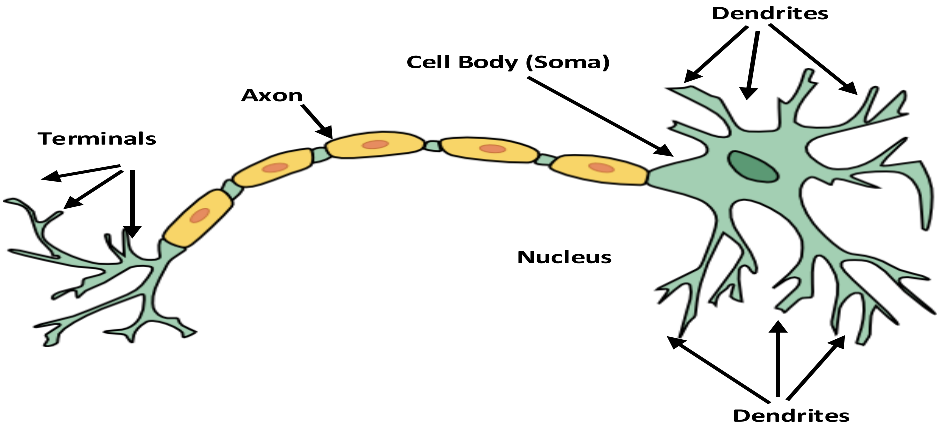


Figure 4-1: Structure of a neuron (Neuroscience Wiki, 2015).

There are three main groups of neurons, motor neurons, sensory neurons and interneurons (Freudenrich and Boyd, 2016). Motor neurons are responsible for carrying information in the form of electrical impulses from the central nervous system, including the brain and spinal cord, to the muscles (Freudenrich and Boyd, 2016). Consider, for example, when a decision is made by an individual to pick up a box. The central nervous system sends messages in the form of electrical impulses to the arm and hand muscles. It causes the arm to move in the direction of the box and also instructs the hand and finger muscles to open and close around the box.

Sensory neurons or receptor cells are responsible for carrying information from the sensory organs to the brain. Interneurons have a more or less mediating role in neuronal terms, as their task is to integrate messages from other neurons (Freudenrich and Boyd, 2016). So, when a message box on a screen is seen, it is the information received from the visual receptor cells in the eye that send the information related to the message box and its appearance to the brain. Human senses rely on various types of sensory neurons to obtain information upon which perceptions are based and this will be discussed in Section 4.2.2.

4.2.2 Human Senses

Generally, it is acknowledged that a human may have only five senses including sight (vision), auditory (hearing), smell (olfaction), touch (tactility) and taste (gustation). However, it is not accurate about the human senses and is rather ambiguous. This is discovered, when studying the human sensation and perception, when thinking of varieties of receptor cells and the way which they perform sensory tasks within the human body (Hiskey, 2010). For instance, Cerretani (2014) has introduced pain, perception of time in different situation and balance as other known human senses.

4.2.3 Sensory Receptor Cells

For the human body to perceive the environment in which it is interacting with, it transforms the external energy (for example light, taste, or sound) via the sensory system into electrical energy by sensory neurons or receptor cells. This process is called transduction. Transduction enables the brain to process this electrical energy meaningfully. Receptor cells in a sensory system are specialised to receive stimuli pertinent to that particular sense. However, receptor cells can sense other stimuli. The resulting effect is always in line with the sense system to which the receptors belong (Lodish, Berk, Zipursky, Matsudaira, et al., 2000). Generally, there are various basic types of receptor cells, but not all of them would perform during interaction with a WMS in a warehouse environment. These include chemoreceptors, mechanoreceptors and photoreceptors, thermoreceptors and nociceptors (Haines and Ard, 2013).

Mechanoreceptors are sensitive to mechanical forces. Perhaps the best known mechanoreceptors are the touch receptors of the skin that are also sensitive to perceive pressure, heat and pain. In addition, the body’s muscles and joints also contain mechanoreceptors. They sense movements such as stretching and rotation of the limbs. Furthermore, the ear, through these mechanoreceptors, enables hearing by receiving the incoming pressure waves, or sound. Mechanoreceptors in the mouth perceive the taste of food as well as general texture of the food (North, 2016).

Photoreceptors are sensitive to light energy received via the eye and convert this energy into electrical information that can be understood by the visual system as shapes, colours and movement (Friedl, 2016). This process will be discussed in detail in Section 4.4.

4.3 The Human Brain

Most animals have a brain typically located in head. But the human brain is an incredibly exclusive organ in comparison with the brain of other animals. Unlike other animals, it gives human the power to communicate, read, write, and problem solve. Additionally, it enables us to perform a large number of tasks including: controlling body temperature, blood pressure, heart rate and breathing; accepting the information about the environment around us via various senses; handling our physical movements; thinking, dreaming, reasoning and experiencing emotions (Freudenrich and Boyd, 2001).

4.3.1 Areas of the Brain

The human brain, spinal cord and peripheral nerves form a complex, integrated information-processing and control system known as the central nervous system (Freudenrich and Boyd, 2001). The central nervous system in the human brain enables an individual to receive various types of information about the environment and performs actions within it purposefully. In the sensory systems, external (for example light, taste and sound) and internal (for example making a decision, feeling tired and or moving fingers) energy are transformed into electrical energy (Jaakko and Robert, 1995). Conducting a study on this field is so vast, therefore the following sections in this chapter only focus on human activities that are involved in interaction with a WMS and performing some daily tasks in a warehouse.

The brain has several different areas. Each area performs a particular type of activity or process. These areas are called lobes. For instance, when a person watches television one lobe works, while another lobe works to control the movement of the legs and arms when walking. Szymik (2011) has mapped the different regions of the brain and the activities they perform, as depicted in Figure 4-2.

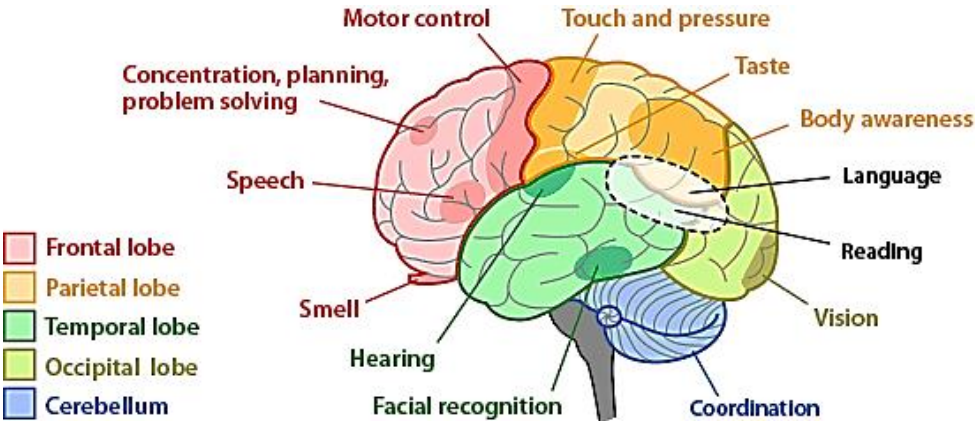


Figure 4-2: The brain areas map (Szymik, 2011).

In addition to activities pictured in Figure 4-2, Szymik (2011) states that the frontal lobe also forms movement of the body, personality, meaning of words and emotional reactions as well; the temporal lobe forms emotions and long-term memory; and the cerebellum controls muscle movements and coordinates the body balance.

4.3.2 Neural Oscillation

The average human brain has over 100 billion neurons and each one may be able to be connected to up to 10,000 other neurons, passing signals to each other (Mastin, 2010). A spike, due to depolarisation (also called the process of discharging $Sodium^+$ and $Potassium^+$ ions as was described in Section 4.2.1) generates tractable signals over time which discloses the brain activity through different parts of the scalp in varying degrees (Draper and Marshall, 2014).

Neural oscillation is a periodic or repetitive neural activity in the central nervous system. Neural activities within the brain can generate oscillatory activity in individual neurons or by formation of a neural interaction. In individual neurons, oscillations can appear either as oscillations in membrane activity or as periodic patterns of spikes. Oscillatory activity in networks of neurons normally appears from feedback connections between the neurons which results in a specific pattern of their spikes. The communication between neurons can raise a different frequency in oscillations in comparison with the spike frequency of individual neurons (Lieff, 2014). Neural oscillation can be observed by the Electroencephalogram (EEG) procedure. Figure 4-3 depicts the location and nomenclature of the intermediate 10% EEG electrodes, as standardised by the American Electroencephalographic Society (Sharbrough, Chatrian, Lesser, Luders, et al., 1991). This can be stated as the most comprehensive standard in comparison with 10 – 20, 10 – 10 and 10 – 5 system standards since it covers the scalp with a greater number of electrodes.

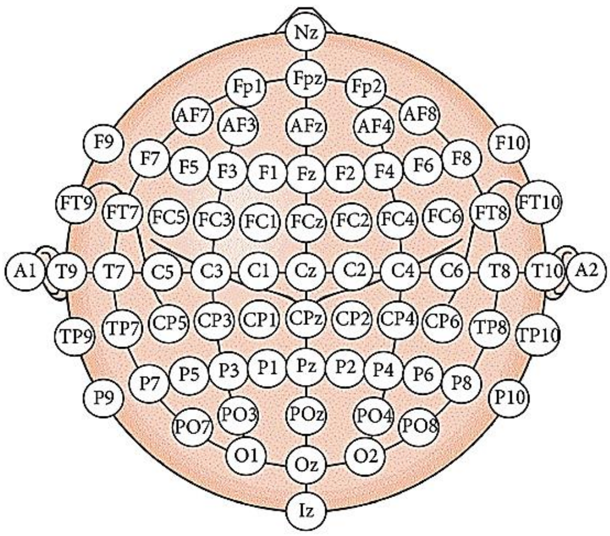
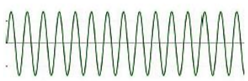
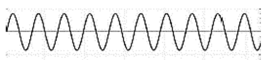
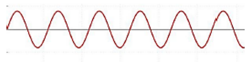
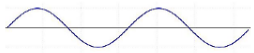


Figure 4-3: Location and nomenclature of the intermediate electrodes, as standardised by the American Electroencephalographic Society (Sharbrough, et al., 1991).

4.3.3 Different Brain Activity Patterns

Table 4-1 represents five different types of brain waves. Baars and Gage (2010) have stated that these waves are linked to cognition, activities and consciousness (Baars and Gage, 2010).

Table 4-1: Brain wave segmentation and associations within each segment (Larsen, 2011; Brainwave Entrainment, 2016; Sharbrough, et al., 1991).

Wave Name	*Frequency Range*	*Associated with*	*Wave Form*
Gamma	> 39 *Hz*	Higher mental activity, including perception, problem solving, attention, cognition and consciousness.	
Beta	13–39 *Hz*	Active, busy thinking, active processing, focused concentration, awakening, memory, and cognition.	
Alpha	7–13 *Hz*	Calm, deep relaxation and disengagement.	
Theta	4–7 *Hz*	Deep meditation, daydreaming, rapid eye movement sleep, feeling deep and raw emotions, creative inspiration.	
Delta	< 4 *Hz*	Deep dreamless sleep, loss of body awareness, immune system, natural restorative.	

4.4 Visual Perception

Vision is most probably the research area related to the sensation and perception related to the interaction with a WMS. As was discussed in Section 1.2, Smart-Glasses are becoming the best known interaction device with a WMS as it has been used in HUD systems. Section 5.2.3 will explain the way Smart-Glasses perform and enable the user to observe information through its visual system. The human visual system can be divided into two different processes that will be discussed below. First, the eyeball receives external light information and transforms it into electromagnetic energy. Second, the brain receives the electrical messages from photoreceptors, processes them and enables the subject to perceive the environment.

Before getting familiar with the human visual system, it is important to have an understanding of what is the nature of light. Observable light can be thought of in two ways. Firstly, as being a collection of many elements called photons that move together at the same speed. Secondly, light may also be identified as being in the form of waves to describe the travel of a massive amount of photons (Allain, 2013).

4.4.1 The Human Eye

Figure 4-4 depicts the structure of the human eyeball which is located in the eye hole of the skull. The cornea enables a human to perceive light in order to observe the environment around itself. The cornea's curving structure can be viewed as a simple lens that contributes to bending light to form an image. A lens forms the given object's light oppositely. The iris and pupil lie underneath the cornea down. The iris is the coloured area of the eyeball and is actually a circle of muscle around the central light entrance, the pupil (Fraser and Gilchrist, 1986). Muscles of the iris cause the pupil to stretch and contract, so opening an aperture of between 2 millimetres and 8 millimetres in the average human eye. The dilation and contraction, firstly allows more light into the eye when the environment is dim and the contraction is less. Secondly, dilation and contraction of the pupil enable that objects observed by a human at different distances from the eye will be always brought into focus (Kam and Power, 2012).

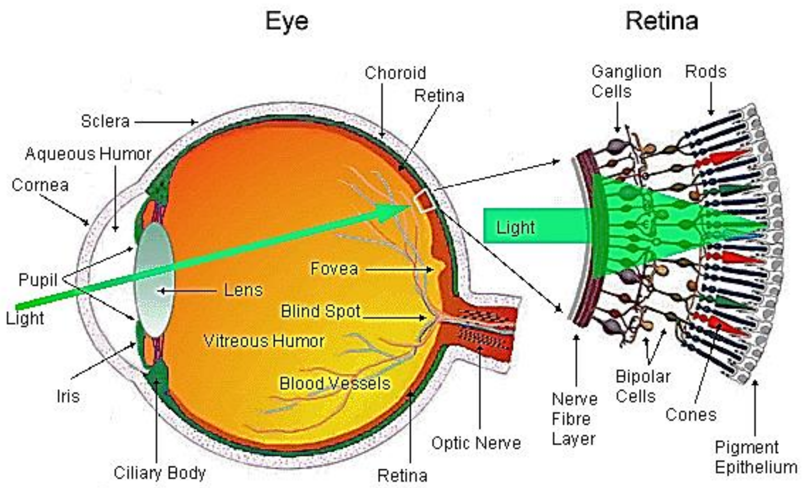


Figure 4-4: The human eye and retina (Kolb, Fernandez and Nelson, 2005).

The lens is located right behind the pupil. All incoming light is focussed by the lens to form an image after passing the cornea and pupil. Ciliary muscles suspend the lens and manipulate the shape of it (Pritchard and Alloway, 1999). The incoming light initially must enter a layer of cells before it can be encoded and then processed. This is the responsibility of the retina to encode the incoming light through a layer of millions of light sensitive cells called photoreceptors. Photoreceptors on the retina carry out the transduction process and in general include rod and cone cells. The human eye has around 170 million rods and 7 million cones. Rods perceive low level light vision and do not process colour information. Cones process colour and also detail (Richardson, 2004).

4.4.2 Mediating Brain Areas

Optical nerves receive visual messages from photoreceptors over the retina and convey them to the thalamus where located between the cerebral cortex and the midbrain, exactly in the centre of the brain. The lateral geniculate nucleus is a part of the thalamus. It divides optical messages into equivalent streams, one carrying colour and shape, and the other carrying contrast and motion. In the occipital lobe at the back of the brain visual information is perceived and processed. The visual cortex locates objects only in horizontal and vertical dimensions. The depth then is mapped in the cortex by merging the signals from both eyes (BrainHQ, 2016; Tsuchitani, 2016). Expanding the discussion on how the visual cortex performs recognition is beyond the scope of this study.

Washizawa, Yamashita, Tanaka and Cichocki (2007), Gao, Wang, Gao and Hong (2008), and Wang, Gao, Hong, Jia, et al. (2008) employed the Visual Evoked Potential (VEP) technique in order to enable brain-computer interaction for different purposes and applications through analysing EEG data. VEP is a response to visual stimuli presented in the form of flushing patterns. By using several flushing patterns with different frequencies, the brain machine interface can be realised (Washizawa, et al., 2007). In all experiments position O1 and O2 (are highlighted in Figure 4-5) were selected to record signals from EEG electrodes. All researchers observed a change in oscillation signals received from electrodes on the visual lobe and occipital cortex.

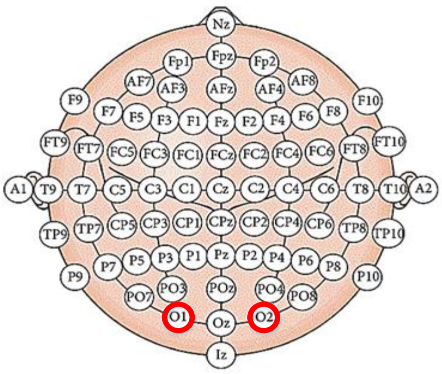


Figure 4-5: The placement of EEG electrodes on the O1 and O2 regions.

Creel (2015), Guy, Ffytche, Brovelli and Chumillas (1999) have reported the greatest blood flow in occipital cortex when evaluating the functioning of the visual path way. In both studies, researchers rather than using EEG to monitor the VEP responses in the brain, employed Functional Magnetic Resonance Imaging (fMRI) technique to scan brain activities.

4.5 Speech Production

Another communication tool that is being used to interact with a WMS either while using Smart-Glasses or a voice headset is speech. These devices receive the sound coming from the user and recognise spoken words. Sound is powered in nature and produced by a vibration of objects in all directions. This vibration changes the pressure density of the air molecules and results in a sound wave production (The Physics Hypertextbook, 2016). A sound is affected by its surrounding environment, external objects and surfaces. It is also can be absorbed by its surroundings. The sound's interaction with the environment causes its perception as different in quality depending on that environment. For example, a normal spoken word will sound physically different if heard in a small room, in a large warehouse hall or out of doors (Burg, Romney and Schwartz, 2013).

Shaffer and Kipp (2013) have broken down the study of language into five elementary mechanisms, they are, phonology, syntax, semantics, morphology, and pragmatics. Phonology is concerned with the sounds that construct a language. Syntax includes the grammatical rules in order to form words into a sentence. Semantics are the actual meaning of a language, morphology specifies how words are formed from sounds and finally pragmatics is the rules for modifying the production of a language in a given context.

Speech production in comparison with visual and auditory perception and recognition involves a more complex process in the brain. This complexity can be seen in Figure 4-6 as Mobus (2016) has mapped this to depict the process of speech production within two general different areas of the brain which are called Wernicke and Broca areas. Wernicke is involved in the production of written and spoken language. Broca is involved in language processing. The final step of language production occurs in the cerebellum where ignite the articulator system as will be explained in Section 4.9.4.

Kamalakkannan, Rajkumar, Raj and Devi (2014) used a 16 channel EEG cap to recognise the part of speech. They tried to study 13 subjects when they imagine the pronunciation of English vowels *'a', 'e', 'i', 'o'* and *'u'* through visual stimulus. FP1, FP2, F7, F8, T9 and T10 areas (Figure 4-7) were reported with more oscillation variance. Activation in these areas during this study confirms the Mobus's map in Figure 4-6 where the subject tries to decide what to say.

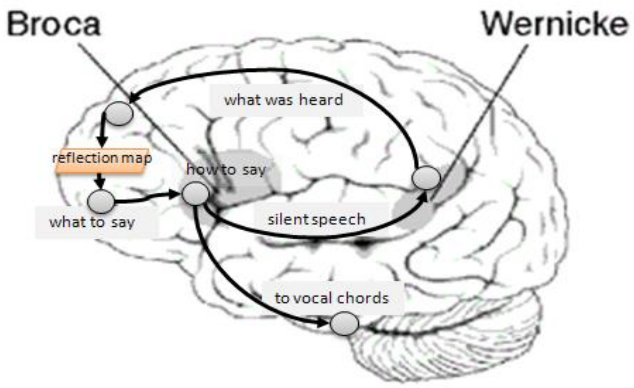


Figure 4-6: The process flow of speech production (Mobus, 2016).

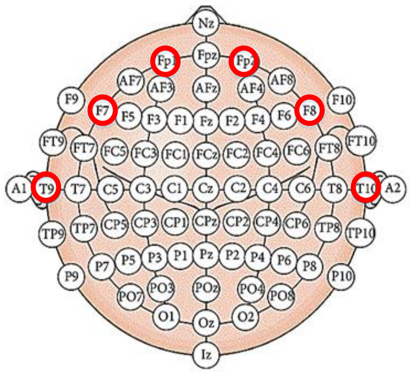


Figure 4-7: The placement of EEG electrodes on the FP1, FP2, F7, F8, T9 and T10 regions.

4.6 Auditory Perception

Smart-Glasses and voice headsets enable communication through the ears by sending voice commands. In Chapter 5 the way these devices generate sound and communicate will be discussed. Here, the structure of the human ear and how it processes the received sound within the auditory system is explained below. The nature of sound was briefly explained in Section 4.5.

4.6.1 The Human Ear

Figure 4-8 depicts the human ear as a cross-section of outer, middle and inner ear. The entire system is responsible for receiving the sound by converting the air pressure vibrations into electrical impulses. The pinna structures the outer ear that is shaped to collect sound from sound sources in the environment. The vibrations of the tympanic membrane are next transmitted to the middle ear. In the middle ear there are three bony structures that amplify the received vibrations and are called ossicles (the ossicles include the malleus, incus, and stapes). The inner ear is filled with a liquid, therefore a greater density is required than the air filled in outer and middle ears. This is why ossicles amplify the vibrations (Freberg, 2009).

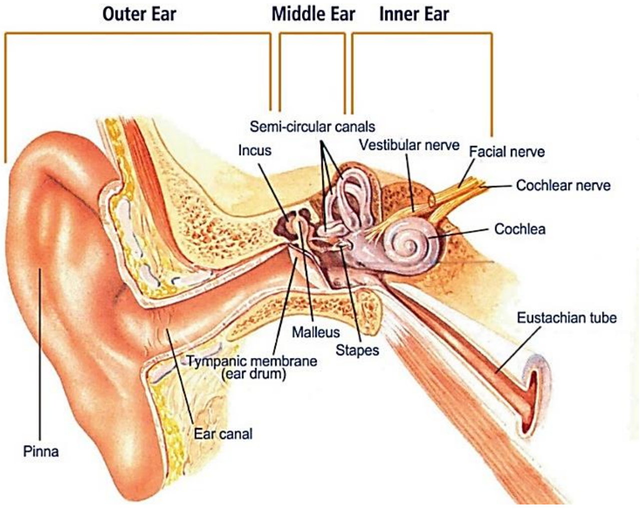


Figure 4-8: The human ear (Hearing Specialist, 2016).

4.6.2 Mediating Brain Areas

The brain receives the messages sent by the cochlea from auditory nerves for further processing and interpretation when the person is either awake or asleep. Groups of neurones in the auditory cortex receive the messages and decode them based on the property of sound. The sound can be soft or loud, high or low, and also can come from different locations. This results in the subject’s experience of hearing or conscious perception. The auditory cortex is located in the superior, posterior, and lateral parts of the temporal lobes (Pujol and Irving, 2016).

Paulraj, Yaccob, Adom, Subramaniam, et al. (2012), Kanoh, Miyamoto and Yoshinobu (2008) enabled direct brain to computer interaction, but instead of employing the VEP method they involved Auditory Selective Attention (ASA). In the ASA method, in comparison with VEP (Section 4.4.2), the brain, rather than responding to a visual stimulus, responds to auditory stimuli. Kallenberg (2007) introduced ASA as a method to enable brain to computer interaction in a different way for the first time. Paulraj, et al. (2012) and Kanoh, et al. (2008) reported a variation of oscillation signals within the auditory cortex. D’ Angiulli, Herdman, Stapells and Hertzman (2008) conducted a research study with the aim of investigating the link between socioeconomic status and brain processes in children using ASA. In this study electrodes were placed on P2, C2, F2, F3, F4, FC3 and FC4 as are highlighted in Figure 4-9.

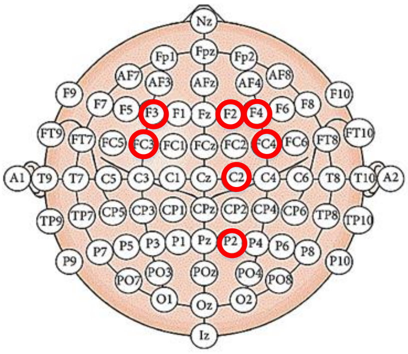


Figure 4-9: The placement of EEG electrodes on the P2, C2, F2, F3, F4, FC3 and FC4 regions.

The Bone Conduction technique, as its name implies, transmits sound waves through the bones into the skull. The vibrations reach the cochlea, or inner ear, which converts them to electrical impulses that travel along the auditory nerve to the brain (Maxwell, 2013). Carvalho, Valente, Duarte, Guimaraes, et al. (2012) have enabled hearing by using electro acoustic stimulation of the auditory system. They used direct cochlear implant by surgical technique to preserve hearing in patients with hearing loss.

4.7 Attention

Incorrect performance of actions causes human errors that can be either intentional or unintentional. An unintentional error can be a skill-based error or a mistake. A skill-based error is caused by action slips or memory lapse and happens when the subject by any reason cannot pay enough attention to performing a task. Action slips occurs while executing a task in a wrong way (NOPSEMA, 2015). Most errors that occur while performing a process in a warehouse can be caused by action slips since available WMSs have minimised the number of human errors that may happen because of memory lapse or mistakes. As Guo, et al. (2015) have discussed in their experiment (Section 1.2), three types of errors may occur by users while fulfilling an order: wrong number, wrong order bin and item mistakes that all may be caused by the lack of attention.

Attention *is the taking possession of the mind, in clear and vivid form, of one out of what may seem several simultaneously possible objects or trains of thoughts. It implies withdrawal from some things in order to deal effectively with others* (James, 1890, p. 403). The locus of attention can be determined in discrete ways, perhaps the most obvious being the act of deliberately opting to concentrate attention on a given object or purpose. However, attention is not always steered by a person’s conscious purposes, as particular kinds of stimuli can automatically capture the attention (Hazeltine, Grafton and Ivry, 1997).

Attention, in general, can be divided into focussed attention and divided attention. Focussed attention arises when the person responds, and processes only one form of stimulus in the presence of a number of different available stimulation sources. In focussed attention, certain types of received sensory information are selected while other information is ignored. Divided attention occurs when more than one stimulus is attended and processed. As an example, when a person is washing dishes while carrying on a conversation (Cohen, 2013).

Liu, Chiang and Chu (2013) recognised the degree of human attention by using EEG signals from mobile sensors during the learning process. They conducted the experiment on 24 subjects, 12 males and 12 females with an average age of 25 years old. They applied a commercial EEG device which covers the forehead with one electrode over the FP1 region (Figure 4-10). As was mentioned before (Table 4-1), attention can also be attained with an increase of beta waves in the frontal lobe (Liu, Sourina and Nguyen, 2013).

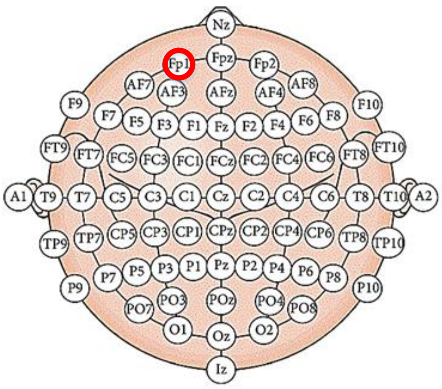


Figure 4-10: The placement of EEG electrodes on the FP1 region.

4.7.1 Automaticity

Training or repetition guarantees a better performance when more tasks have to be carried out at the same time, because task becomes automatic execution (Ebben, Kindler, Chirdon, Jenkins, et al., 2004). This means that performing the task requires less attention. Spelke, Hirst and Neisser (1976) asked schoolchildren reading stories to take dictation of words at the same time. The students found this very hard and both tasks, writing of the dictated words and understanding the stories unsurprisingly were poor when examined. After they passed a six weeks training of five hours per week on the tasks, performing the dictation became relatively automatic.

4.7.2 Action Slips

It is generally acknowledged that when the number of tasks a person is required to attend to is increased, there is a certain number of mistakes in that person's performance (Duncan, 1993). Attention then is a critical factor in everyday functioning and can also guarantee how accurately tasks are carried out.

Reason (1990) identifies action slips as unintentional actions that happen to an individual. It is also clear that these occur the most during routine, well-known actions and tasks. Reason conducted an experiment on 35 individuals and asked them to keep a record of their action slips for four weeks. Reason categorised them into five categories:

1. Storage failures – such as trying to fill a teapot twice (40%).
2. Test failures – going to perform a task and doing something else, such as going to turn on the kettle but instead turning on the radio (20%).
3. Sub-routine failures – forgetting part of or mixing up the sequence of smaller actions within an action such as making a pot of tea and forgetting to put in the bags (18%).
4. Discrimination failures – mixing up objects used for different purposes, such as putting shaving foam on a toothbrush (11%).
5. Programme Assembly failures – incorrect combination of actions such as peeling a banana and throwing away the fruit rather than the skin (5%).

4.8 The Human Brain and the Counting Action

Counting is a basic property of the environment that can be performed by estimation (subitising) as well. Even some animals have the ability of estimating and representing the quantity of given objects. Counting aims to certify a precise representation of a number of given items. As was stated as a factor which causes the problem (Section 1.2), most order-picking errors occur while counting required items even when the user uses HUD system. Therefore, it is important to understand how the human brain carries out counting tasks. In general, the process of counting given items, occurs within three different sub-processes in the brain, namely, estimation, subitising and counting.

Estimation is the process of finding an estimate, or approximation, which is a value that is usable for some purpose even if input data may be incomplete, uncertain, or unstable. Subitising is the rapid, accurate, and confident judgements of numbers performed for small numbers of items, up to about four, without counting them. Counting is the action of finding the number of elements of a finite set of objects. The differences between the verbs enumerate and count is that enumerate is to specify each member of a sequence individually in incrementing order while to count is to enumerate the digits of a numeral system (Wikidiff, 2016).

Demeyere and Humphreys (2007) have stated that visual counting and estimation are different attentional mechanisms. They also mention how colours and shapes of items can influence the result of counting or estimation positively. Chong and Evans (2011) suggest that focused attention is more suitable for enumeration, whereas a divided attention is better for estimation. On the other hand, Burr, Turi and Anobile (2010) have conducted an experiment involving reducing the number of given items when subitising and estimation. They discovered that subitising and estimation are not identical operations. They believe that pre-attentive estimation mechanisms work in all situations, but in subitising, attentive mechanisms also play an undeniable role.

What an order-picker has to apply during an order-picking count task is not necessarily estimation or subitising the picked items, but what is necessary is a precise and accurate counting of them. However, it is possible that this happens unintentionally. Therefore, it is significant to perform such a task with a high level of mindfulness and concentrate the focused attention on the given task. *Mindfulness is a state of consciousness in which the practitioner maintains a single pointed awareness focused on mental* (Mars and Abbey, 2010, p. 56).

4.9 Human Movement

When a person decides to move a body part intentionally, for instance arms, legs and even necessary muscles to produce speech, the brain creates appropriate commands within the cerebellum as was introduced in Section 4.3.1. The human muscles are attached to bones and joints. The human brain processes the intention of a movement in the cerebellum located in the lower area of the brain, below the pons and sends an electric impulse to the relative muscles through the nervous system (Everett and Kell, 2010). In response to this signal, the muscles contract and create body movement (Saponas, Tan, Morris, Balakrishnan, et al., 2009).

While studying these factors, it is significant to consider the study of motor skills as well as the biomechanics of human movement. *A motor skill is a function, which involves the precise movement of muscles with the intent to perform a specific act* (Educlime, 2016). *Biomechanics is the study of how the systems and structures of biological organisms react to various forces and external stimuli. In humans, biomechanics often refers to the study of how the skeletal and musculature systems work under different conditions* (Sailus, 2016). However, the study of the entire different motor skills and biomechanical factors does not appropriately fit into the scope of this study.

During discussions in this section, the term Electromyography (EMG) will be used frequently. EMG is a procedure which assesses the activities of body muscles and motor neurons. Motor neurons transmit electrical signals that cause muscles to contract. The EMG method receives signals using surface EMG electrodes and translates these signals into graphs, sounds or numerical values that a specialist interprets (Mayo Clinic, 2016). Researchers often use this method to study the human muscular activities.

4.9.1 Manual Materials Handling

Manual Materials Handling (MMH) can be performed by applying different methods while moving a load. In a semi-automated warehouse, the labourer uses his/her hand(s) to apply a method and move a load. Mital, Nicholson and Ayoub (1997) list the usual MMH methods to include lift, push, pull, carry and hold with hand(s). However, all these methods can be applied in moving various sizes of loads. Lift is the main method which would initiate a movement. The labourer needs to pick an item out of the storage area before any other acts by lifting it.

The bones of the human body can be known as levers activated by a group of specific muscle contractions. This enables the body to make a movement and even move different objects. Naturally, the human implements the principles of physics to control the necessary amount of strength of the muscles. Figure 4-11, for example represents biomechanics of an elbow when holding a box. This method of handling a load, pushes a force on the elbow and uses the power of forearm and biceps (Anderson, 1995).

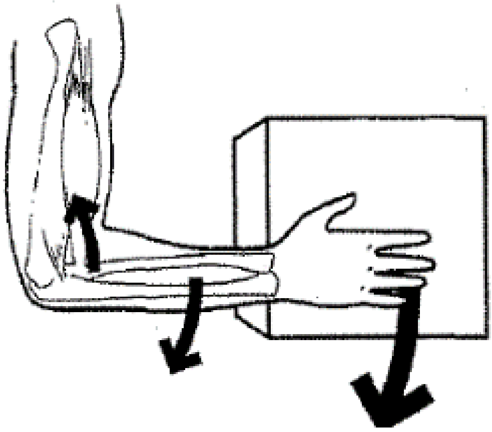


Figure 4-11: Biomechanics of the elbow (Anderson, 1995).

Muscles contractions while lifting up can be either isometric, concentric or eccentric. An isotonic contraction can be either concentric or eccentric. Concentric (Figure 4-12-a) contraction occurs when the motion is in the direction of the contraction and oppositely, eccentric (Figure 4-12-b) motions occur when the motion happens in the reverse direction. Isometric contraction (Figure 4-12-c) involves muscular contraction against moving an object in which the length of the muscle changes, for instance holding a book without moving results in this type of contraction (Tortora and Derrickson, 2014).

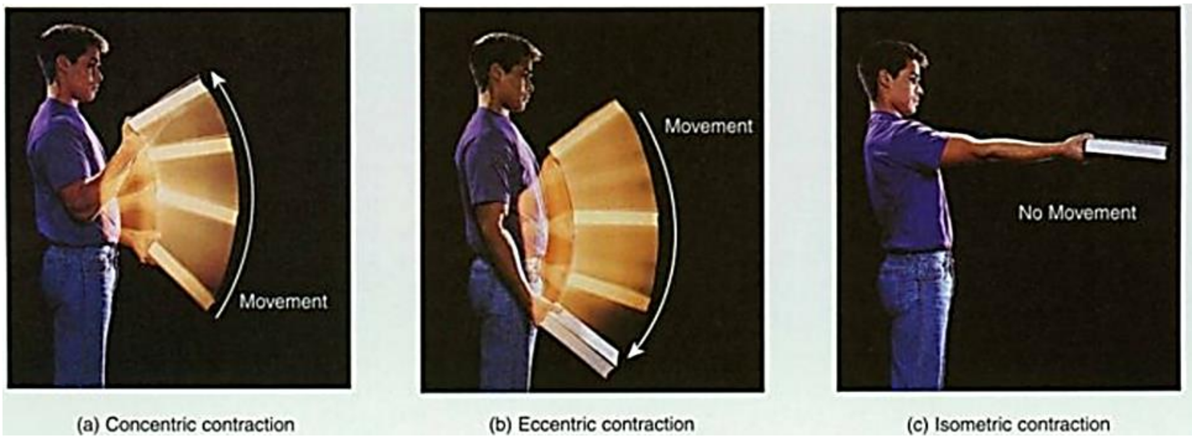


Figure 4-12: Comparison between isotonic (concentric and eccentric) and isometric contractions (Tortora and Derrickson, 2014, p. 314).

Linnamo (2002) has presented an analysis of EMG signals when the subject moves arms concentrically and eccentrically. The results show the stress on forearm and biceps muscles when performing an isotonic movement. This can result in receiving noisy EMG signals over the forearm muscles since all bicep and forearm muscles are under the stress.

4.9.2 Hands and Finger Gestures

Gestures include movement of the hands, face, or other parts of the body. A gesture is known as a form of non-verbal and non-vocal communication method in which visible bodily actions communicate particular messages (Kendon, 2004). Chen, Zhang, Zhao and Yang (2007) used EMG surface electrodes and 2-D accelerometers to recognise the muscular contractions when forming various finger gestures. Their system was capable of recognising the extension of each individual finger's movement. They used accelerometer sensors (Section 5.5.2) to recognise wrist and hand movements.

Figure 4-13 depicts the muscular anatomy of the human forearm and how it comprises different muscles. The forearm muscles, in order to assist the bending and straightening of the fingers slide the tendons attached to the fingers. Therefore, to posture a gesture using fingers, necessarily the forearm muscles must be contracted and relaxed (Innerbody, 2016).

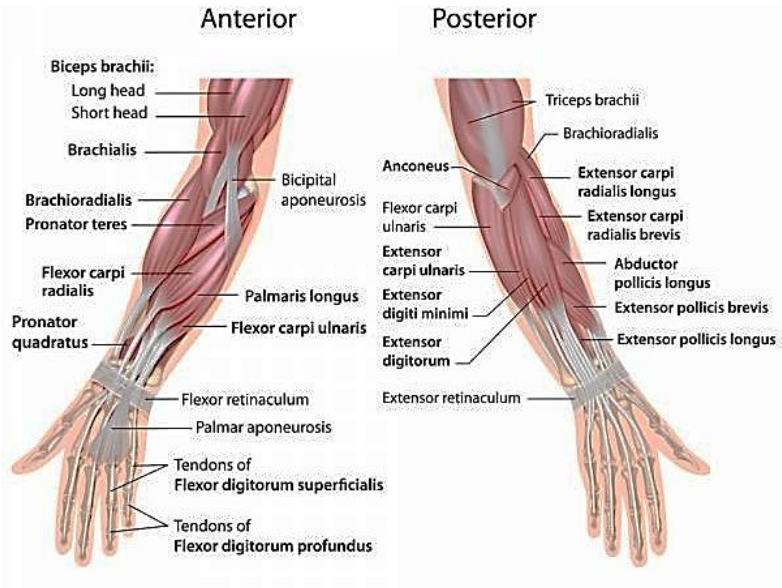


Figure 4-13: Muscles of the forearm, right hand (Thomas, 2016).

Researchers in the Backyard Brain institute have analysed EMG signals collected from different finger movements in order to control a robotic hand. They placed 5 EMG electrodes on the forearm as it can be seen in Figure 4-14 below and asked subjects to move different fingers. The data classification result of each task is graphed under the task. The data classification results can indicate different muscular activities within the forearm when moving different fingers (Backyard Brains, 2016).

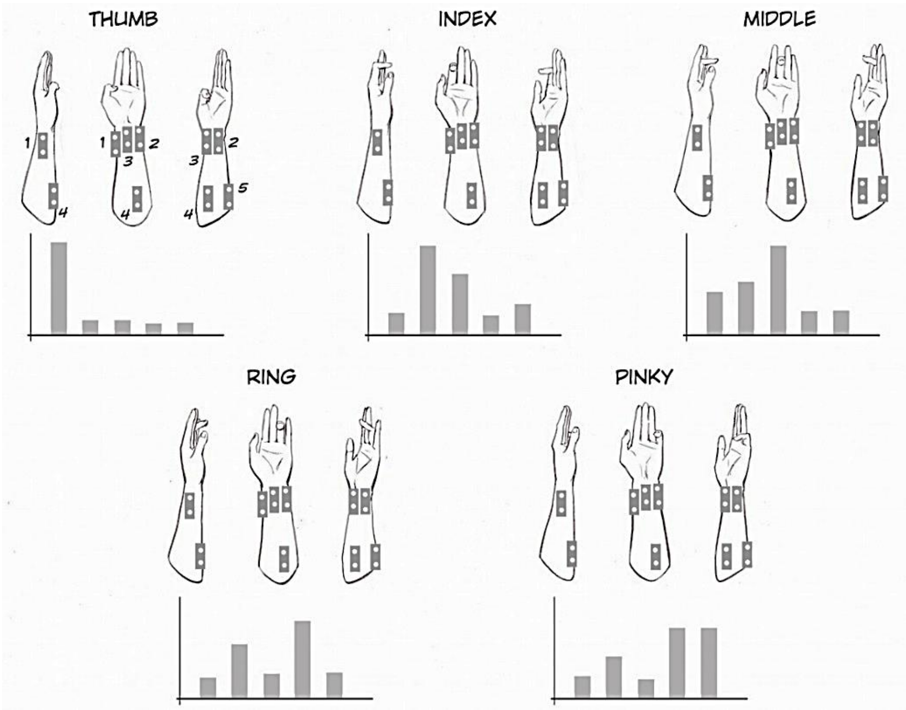


Figure 4-14: Electrodes placement on forearm and data classification results when moving different fingers (Backyard Brains, 2016).

One significant advantage of applying the EMG technique to recognising different gestures is presented by Saponas, et al. (2009). They observed changes on EMG signals in both hands-free and hands-full situations when subjects postured the similar gestures with their fingers. While performing hands-full tasks, participants were asked to squeeze their fingers while holding one ball or one mug in their hand. They identified the use of EMG technique as an always available input with Muscle-Computer Interfaces.

4.9.3 Speech Production

When the human speaks, he/she produces different sounds which are the result of muscles contracting. The body pushes the air out of the chest by using the muscle in it. The flow of air is the most fundamental requirement for the most of speech sounds. Then muscles in the larynx modify the air flow when it is traveling from the chest to the mouth and nostrils (Roach, 2009).

The lips are important in speech. They can be pressed together (when we produce the sounds ‘p’, ‘b’), brought into contact with the teeth (as in ‘f’, ‘v’), or rounded to produce the lip-shape for vowels like ‘u’. Sounds in which the lips are in contact with *each other are called bilabial, while those with lip-to-teeth contact are called labiodental* (Roach, 2009, p. 10).

Figure 4-15 represents the muscular anatomy of a human face. Researchers in The Cognitive Systems Laboratory at the Institute for Anthropomatics of the Karlsruhe Institute of Technology placed EMG surface electrodes on the muscles that are engaged when both lips and jaw move to form sounds and produce speech. As the result of analysing data they successfully invented a Silent Speech Interface (SSI). SSI reads signals from potential articulatory muscle activities and translates them into text when the subject speaks even noiselessly. They have picked up the signals from *the levator angulis oris, the zygomaticus major, the platysma, the orbicularis oris, the anterior belly of the digastric, and the tongue* (Wand and Schultz, 2011, p. 297).

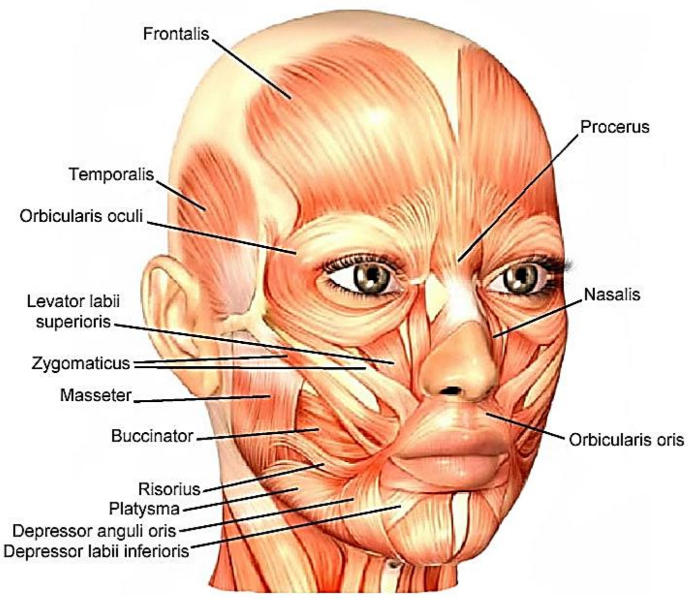


Figure 4-15: Different muscles in the face (Hair and Makeup Artist, 2016).

4.10 Conclusions

This chapter attempted to introduce different human factors that are involved in the interaction with a WMS as well as in performing daily operations in a warehouse with the aim of answering the second research question which was defined in Section 1.4 (*What human factors are involved while performing daily operations in a warehouse?*). Finding an answer to this question serves two purposes. First getting familiar with the human sensory system and the way it allows humans to perceive, communicate and understand the external world. Second, designing a system that requires less effort to interact with and can perform in even in a noisy environment when both hands are busy.

In order to achieve the first aim, a definition of senses was given in Section 4.2. Then, the visual system (Section 4.4) including the human eye (Section 4.4.1) and visual perception (Section 4.4.2), auditory system (Section 4.6) including the human ear (Section 4.6.1) and sound perception (Section 4.6.2), speech production (Section 4.5) including required muscular activities (Section 4.9.3) linked to speech and planning it were discussed. This information is necessary to understand the interaction with a WMS using sensory information including sound and light.

In addition, focusing attention (Section 4.7) on a specific task was introduced as a necessary factor which helps the human perform a task as accurately as possible. Focused attention was introduced, and also its application was suggested as a solution to reduce the counting errors in Section 4.8.

Table 3-2 in Chapter 3, presented a comparison of the latest automation technologies used in a warehouse in which interaction with a WMS is established. In order to achieve the second aim, Table 4-2 presents human factors that are engaged in interaction with a WMS using these technologies. As was identified in Section 3.6.6, Smart-Glasses used in the HUD method are equipped with a variety of movements and orientation sensors. This can enable solution designers recognising head gestures to create inputs as well. During the study of available solutions in literature, there was no report of such an application in the warehouse environment.

Table 4-2: Warehouse automation technologies and the human factors involved.

	Hands/Fingers	*Visual*	*Auditory*	*Verbal*	*Gesture*
Bureaucratic	✓	✓	✗	✗	✗
Handheld RF Scanner	✓	✓	✗	✗	✗
Handheld Barcoding System	✓	✓	✗	✗	✗
Lightening	✓	✓	✗	✗	✗
Cart-Mounted Display	✓	✓	✗	✗	✗
Voice Headsets	✗	✗	✓	✓	✗
HUD	✗	✓	✓	✓	???

Table 4-3 below, presents a summary of necessary information which investigates the possible use of different surface electrodes in order to establish interaction with a

WMS with the aim of improving the usability of current technologies in a warehouse environment.

Table 4-3: Enabling interaction sensory sensors.

	Body Part	*Type of Electrodes*	*Electrodes Placement*
Speech Production	**Wernicke and Broca areas**	EEG	FP1, FP2, F7, F8, T3 and T4
	Face Muscles	EMG	Levator angulis oris, zygomaticus major, platysma, orbicularis oris, anterior belly of the digastric, and tongue muscles
Attention	*Body Part*	*Type of Electrodes*	*Electrodes Placement*
	Frontal lobe	EEG	FP1
Gestures	*Body Part*	*Type of Electrodes*	*Electrodes Placement*
	Moving body parts	EMG	Forearm muscles
	Moving body parts	Accelerometer	Behind ears

Using accelerometer sensors on fingers also can facilitate gesture recognition, but when both hands are busy, creating a movement might not be feasible. This study ignores the use of bureaucratic, handheld RF/barcode scanner, lightening and cart-mounted methods as they are introduced as significantly slower systems when their performance is compared (Section 1.2). In addition, these methods do not allow hands-free task performance.

The next chapter uses information from Table 4-3 and investigates the possible sensory technologies that could lead the study to design a solution. In addition, as was mentioned in the scope and limitation of this study (Section 1.6), the following chapter will investigate how to offer a solution for the main problem by using available sensory solutions on the market.

Chapter 5. Sensory Technologies for Human-Computer Interaction

Objective(s) of Chapter

1. *Investigating the sensory technologies commercially available for HCI.*
2. *Introducing the latest technologies for visual, verbal, auditory and gesture interaction methods.*
3. *Selecting an appropriate sensory technology to design the solution.*
4. *Describing and explaining the procedures involved in the development of a human-computer interface using biomedical signals.*

Structural Overview of the Chapter

Chapter 1: Introduction

Chapter 2: Research Design

Chapter 3: Warehouse Management and Automation Technologies

Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems

Chapter 5: Sensory Technologies for Human-Computer Interaction

5.1 Introduction
5.2 Visual Interaction
- 5.2.1 Interaction Using Electronic Visual Display
- 5.2.2 Virtual Reality
- 5.2.3 Augmented Reality
- 5.2.4 The Future of Visual Interaction

5.3 Verbal Interaction
5.4 Auditory Interaction
5.5 Gesture Interaction
- 5.5.1 Image Processing
- 5.5.2 Motion and Orientation Sensors

5.6 Direct Neural Interaction
5.7 Bio-Signal Acquisition
- 5.7.1 Applications and Bio-Signal Acquisition for a Muscle-Computer Interface (MCI)
  - 5.7.1.1 EMG Electrodes
  - 5.7.1.2 MYO Armband
- 5.7.2 Applications and Bio-Signal Acquisition for a Brain-Computer Interface (BCI)

5.8 Signal Processing and Feature Extraction
5.9 Machine Learning for Classifying Bio-Signals
5.10 Conclusions

Chapter 6: Design and Evaluation of the Solution

Chapter 7: Conclusions and Future Research

5.1 Introduction

In recent years, Human-Computer Interaction (HCI) has become an important field of study and has improved human performance by interacting with computerised systems. In order to keep track of necessary procedures within the DSR methodology, this chapter aims to investigate available HCI technologies which would assist to design an IT-based solution to cover the main problem. As was discussed in Section 1.2, the problem occurs when a user interact with a WMS in a warehouse environment.

This chapter will investigate some interaction technologies, techniques and devices which enable a user to interact with a machine by using his/her natural biological sensory system (Chapter 4) including: visual (Section 5.2), verbal (Section 5.3), auditory (Section 5.4) and gesture posturing (Section 5.5) capabilities. This will include those devices and techniques which specifically use sensory technologies and their different applications in the real-life that have already been reported on or are not yet available on the market but will be released in the near future.

This chapter will furthermore focus on some HCI techniques which establish Direct Neural Interaction by sensing and detecting specific biological behaviours of the user. In order to introduce the way this HCI method can be designed and developed, Section 5.7 will explain techniques, used and reported frequently, to detect and sense different biological behaviours of the user by acquiring biomedical signals (bio-signals). In addition, in Section 5.8, the methods that must be used for processing the bio-signals to extract meaningful features from will be introduced. Section 5.9 will introduce Machine Learning (ML) as a technique which enables a direct neural HCI system to recognise patterns in biological behaviour of a user.

Section 5.10 will conclude by suggesting some possible combinations of technologies and techniques which may appropriately offer a solution to the main problem. In addition, this section provides a brief summary of some procedures which will assist this research study to initiate the design and development of the IT-based artefact.

5.2 Visual Interaction

Popular WMSs on the market provide necessary information on a screen opposite the user’s eye where the conversion of data on the screen into neurological data occurs and enables the human to observe information (Section 4.4). The WMS through this method enables the user to perform a functionality (a list of functionalities was provided in Section 3.4.2) and use information on the screen. In general, modern WMSs establish a visual interaction by using a screen or augmented reality. This section discusses different interaction methods that have found their way into the warehouse industry as well as new technologies that will also be used in the near future with the aim of facilitating and improving this type of interaction.

5.2.1 Interaction Using Electronic Visual Display

Section 3.6 introduced the automation and communication techniques which use human visual interaction as one component of the interaction process with a user. Modern warehouse solution designers have integrated automatic identification and recognition techniques (Section 3.5) with Electronic Visual Display (informally known as a screen) with the aim of enabling the user to communicate with a WMS in time and in location. For instance, mobile barcode/RF scanners are equipped with touch screen display, different wireless communication devices, different sensors and an Operating System (OS). This has improved the capabilities of a normal scanner on a mobile device with the ability of running apps. In addition, users can provide inputs to the system using the touch capability.

Figure 5-1: Rugged industrial tablet computer (Data Respons Co., 2016).

Figure 5-2: Tousei Tech TS-901 scanner (Precision Technology Co., 2016).

As two examples, Figure 5-1 presents the M101B tablet computer produced by Data Respons Co. (Data Respons Co., 2016) and Figure 5-2 presents TS-901 mobile RF/Barcode scanner produced by Tousei Tech Co. (Precision Technology Co., 2016). The solution designers are able to design Android/Web-based apps for both devices. And the M101B supports Microsoft Windows Mobile OS as well.

A problem with using touch screen technology is that it reduces the hands-free (Newcomb, Pashley and Stasko, 2003) and eyes-free capabilities of the user. The user has to use fingers of one hand to interact with both types of device, while using the other hand to hold the device. The user constricts his/her field of view to the display which results in missing the perception of peripheral information in the real world while providing inputs to a touch screen (Hincapie-Ramos and Irani, 2013).

5.2.2 Virtual Reality

The Virtual Reality (VR) Society website defines VR as a method with the purpose of presenting graphics with a three-dimensional, computer-generated environment to a user (Virtual Reality Society, 2016). In comparison with normal displays, the VR uses a stereoscopic display to present graphics to the user. Figure 5-3 presents the hardware components used in VR which form a stereoscopic display using two normal displays and convex lenses that enable a very wide field of view. The presentation method induces a sense of presence to the user with a combination of other human interaction abilities such as the auditory, speech production and movement and enables interaction with the environment (Jackson, 2015).

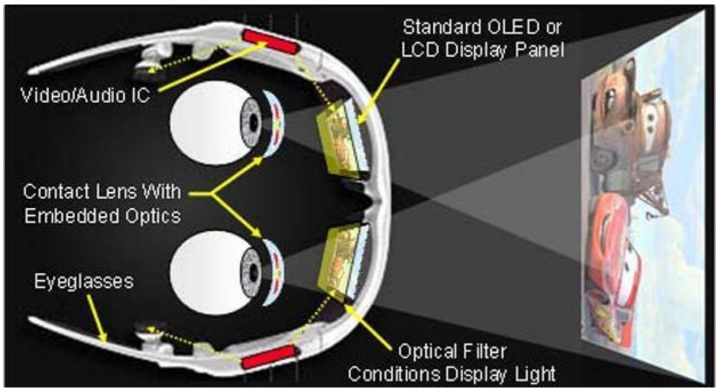


Figure 5-3: Virtual Reality hardware components (Iliaifar, 2012).

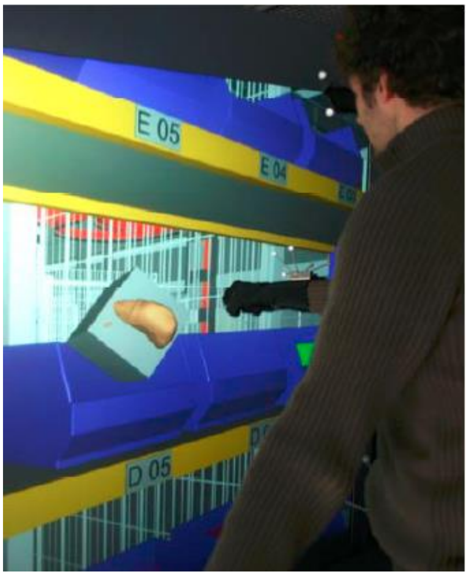


Figure 5-4: Order-picking simulation using Virtual Reality (Reif and Walch, 2007).

VR is becoming an increasingly interesting technique as it has found its way into different industries successfully. In Figure 5-4, an application of VR in the field of warehouse management is presented. Connecting a complementary input provider device such as a data glove (Section 5.5.2) and a self-regulating treadmill to the VR system leads the user to interact with an immersive workspace. This can simulate different functionalities of a WMS. The data glove allows for moving objects between holding units and the treadmill allows for walking through the simulated warehouse building. The use of VR in warehouse management results in optimisation of planning costs and improves the training process (Reif and Walch, 2007). Dede (2006) introduces the use of VR as a training tool which improves the process.

In order to develop an application for the VR, designers must follow two main stages. Firstly, to design the graphical presentation of the environment and secondly, to enable interaction by using interaction tools. *The VR combines the normal screens with depth cues such as parallax (objects in the distance moves slower than closer objects), converging lines and shading* (Jackson, 2015) and at the end wraps the image into the barrel-distorted shape (Pohl, 2014). This process can be done by using a 2D/3D graphic rendering technique such as OpenGL and Direct3D Application Programming Interface (API)s. This type of API usually interacts with a Graphics Processing Unit (GPU) to accelerate the rendering process (McMenemy and Ferguson, 2007).

In order to enable an interactive environment for the user, VR uses additional components which mainly aim capturing human movements. For instance, Noor Adnan and Rafiqul (2012) have presented the application of the gesture recognition using image processing techniques and a camera, Rorke, Bangay and Wentworth (1998) have presented the application of a virtual stick and Thalmic Labs (2015) have presented the application of MCI, as well as capturing motion and the orientation of the forearm within the VR's environment.

5.2.3 Augmented Reality

Gill (2015) introduces Augmented Reality (AR) as *the cousin of VR which maintains the real physical reality and adds a digital element to create an environment that becomes a value-added mix of the real and the virtual* (Gill, 2015). The use of Smart-Glasses (in the field of warehouse management, it is also called HUD – Section 3.6.6) within the AR has become more popular as it has enabled an eyes-free and hands-free interaction between the user and a computer application.

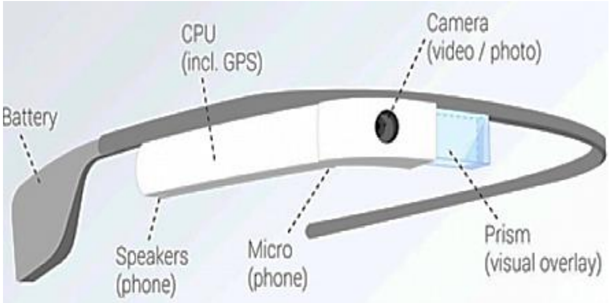


Figure 5-5: Hardware components of a Google Glass (Innovation and Gadgets, 2013).

Figure 5-6: Kopin Smart-Glasses display (Kopin Corporation, 2016).

In Figure 5-5, Google Glass is presented as an example of the available Smart-Glasses on the market. Kopin Co.[2] (2016) one of the world's leading developers and providers of technologies, has designed and developed the world's smallest prism display called Cyber Display (Figure 5-6). The Smart-Glasses render graphics inside its GPU and then projects the graphics directly into the user's pupil, onto the retina, where the person transmits the light energy into neural data (as was explained 4.4) using a prism display. Most Smart-Glasses receive pictures and sound from the real world by means of a built-in camera and microphone. This can increase the ability of a user to interact with the AR environment.

Developing an application for Smart-Glasses varies based on the products' specifications. Smart-Glasses run applications through their built-in OSs (for instance, Google Glass uses Glass OS and Vuzix Glass uses Android). For configuring and managing the Smart-Glasses, there are different methods such as using Smart-Phone apps and motion detectors. There are various design patterns and guidelines that developers can follow for more efficient development of Smart-Glasses (Google, 2016a). Designers must follow the same procedures they follow for designing for a normal screen, but design for Smart-Glasses is constrained by the resolution size of the prism display (Razvan, 2015).

The Smart-Glasses can recognise the real-world objects around the user by processing the captured images from the camera. In addition, the use of location, motion and orientation sensors has enabled the AR to add a wider range of data to the real world beyond the field of the user's exploration. This data is identified based

[2] Kopin Cooperation supplies Vuzix (Leading Developer of Smart-Glasses and Video Eyewear) with hardware. SAP, the market leader in enterprise application software, announced its AR applications with Vuzix Smart-Glasses. (Accessed on 4 May, 2016)
[Kopin Co., website: http://www.kopin.com/]
[Vuzix Co, website: https://www.vuzix.com/]

on the geographical placement of objects. For instance, Figure 5-7 presents the environment which the user explores through AR. Information added to this environment is specifically designed for this part of the building. In this example, AR has highlighted conveyors and is presenting a movement of different virtual objects.

Figure 5-7: An environment imposed with the virtual objects (Reif and Walch, 2007).

5.2.4 The Future of Visual Interaction

Microsoft announced the first edition of HoloLens in a Microsoft Store on 30th March 2016 which is compatible with most OSs, such as Android, iOS and OSX (as is shown in Figure 5-8). In comparison with the Smart-Glasses, HoloLens uses a high-definition stereoscopic 3D optical head-mounted display to impose 3D holograms with what the user explores. HoloLens allows a user to interact with gaze, voice, and hand gestures. In addition to a GPU, HoloLens uses a Holographic Processing Unit that process 3D images before projecting them on the frontier lens as a hologram. The user is able to manipulate holograms in a natural way. HoloLens is able to offer evolutionary solutions for 3D modelling (Figure 5-9), business (Figure 5-10), music, games, entertainment and other activities. In order to develop an application for HoloLens, the developer can create images by using 2D/3D graphic rendering technique such as OpenGL and Direct3D APIs (Microsoft, 2016).

Figure 5-8: Microsoft HoloLens (cNet, 2016).

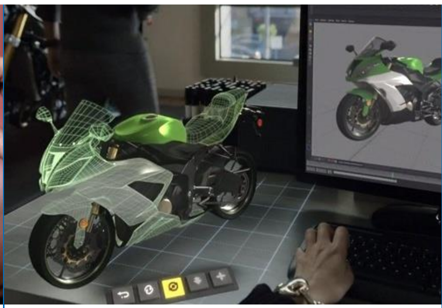


Figure 5-9: Application of HoloLens in 3D modelling (Tyrsina, 2015).

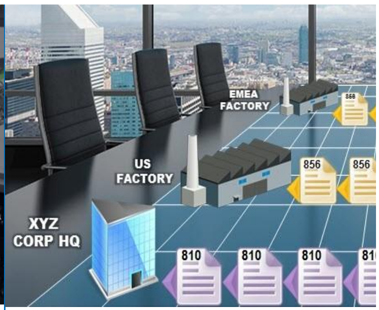


Figure 5-10:Future of workplaces with HoloLens (Morley, 2015).

Amir Parviz (2009), a University of Washington electrical engineering professor, introduced a successful working prototype of a wireless controlled bionic contact lens display that covers the pupil with a semi-transparent Light-Emitting Diode (LED)s (each LED chip is 300 *μm* in diameter). Figure 5-11 presents the bionic contact lens, designed by Amir Parviz. He believes, in the future contact lenses will become a real platform (Amir Parviz, 2009).

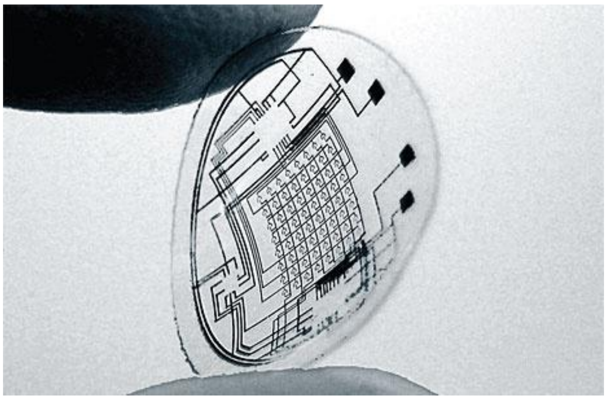


Figure 5-11: Augmented Reality contact lens (Amir Parviz, 2009).

5.3 Verbal Interaction

As was explained in Section 1.2, the use of Smart-Glasses (using vision and sound) is known as the most efficient technique to communicate with a WMS. However, in a noisy environment, the available Smart-Glasses on the market cannot establish interaction with the user by using a voice recognition system. The voice is known as one of the most natural methods of communication between humans. The use of voice headsets as a popular interaction method with the WMS has solved the existing problem (Quantum Software, 2016).

Robocom (2016), a leading provider of Supply Chain Management solutions, introduces four main components within a warehouse voice headset which enable the headset to be used as an HCI tool:

1- ***Hardware* –** A wireless terminal wearable which a user typically wears in a belt pack, with a headset and microphone connected to the terminal.
2- ***Voice Speaker* –** A speaker that transfers voice commands and instructions to the user through the headset.
3- ***Voice Recognition* –** The user normally provides inputs to the application by reading a check digit, then confirms the validity of input. Various commands can be used for modifications or other problems that may occur***.***
4- ***Voice server* –** A server with the aim of main application that organises inputs to an application and manages an efficient interaction with the voice terminals.

Figure 5-12 shows a voice headset in addition to its terminal. Modern microphones used in headsets use various noise cancellation software and hardware to extract the desirable sound signals out of the received signals from a microphone. Noise cancellation can be carried out with software, as well as by hardware.

Figure 5-12: Voice headset (Quantum Software, 2016).

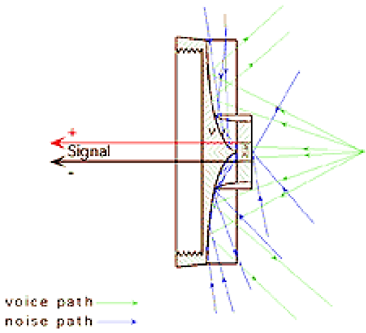


Figure 5-13: Voice path through theBoom microphone (theBoom, 2016).

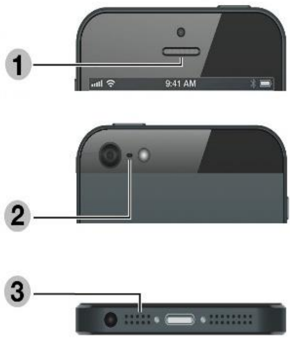


Figure 5-14: Microphones in the Apple iPhone 5 (Easy Computer Tutorial, 2016).

Figure 5-13 presents the noise cancellation technology used in "theBoom" company's microphones and headsets. As this figure depicts, the microphone is able to focus only on receiving signals from the user and not from the source of noise (theBoom, 2016). The Apple Company employed multiple microphones (Figure 5-14) in its phones and tablets to recognise noise in the environment. This can improve the extraction of the user's speech from the received sound signals in any environment.

The Whisper audio chip, was designed by Kopin and in comparison with other audio chips, applies a novel noise cancellation technology and voice extraction filter. This chip has improved the performance of Smart-Glasses' Automatic Speech Recognition (ASR) and has enabled them to recognise speech at any noise level even when the user speaks with a low or normal voice (Whisper™ Chip, 2016).

Basically, the ASR is an application of a machine learning technique with the aim of recognising speech out of sound signals. The major components of the ASR are (Deng and Li, 2013):

1. Feature extraction;
2. Acoustic modelling;
3. Pronunciation modelling;
4. Language modelling; and
5. Hypothesis search.

Expanding the way ASR works is beyond the scope of this study, however, a few feature extraction and machine learning techniques will be introduced in Sections 5.8 and 5.9.

5.4 Auditory Interaction

Sound is a popular output of the computer in which the computer generates audio signals via its sound card and a speaker in order to interact with the auditory system of the user. As was explained in Section 3.6.5, voice headsets are equipped with headphone to transfer information from the computer to the user. In comparison with normal speakers and headphones which transmit the audio signals to the human outer ear, where the process of auditory perception starts, Google Glass uses the Bone Conduction technique (Section 4.6.2) to transduce the auditory information as vibrations directly into the inner ear, through the skull (Google, 2016a).

A computer in order to interact with the external world and provide information, occasionally uses auditory interaction. This is done sometimes by Speech Synthesis technique which basically is an artificial production of the human speech. A Text-to-Speech system translates normal language text into speech by applying a Speech Coding technique. Synthesisers are used to make more natural speech by rendering symbolic linguistic representations like phonetic transcriptions into speech (Allen, Hunnicutt and Klatt, 1987). According to Arjona Ramírez and Minami (2003), a

Speech Coding technique models digital audio signals by considering some speech-specific parameters. The model would then be combined with generic data compression algorithms to represent the resulting, modelled parameters in a compact bit stream.

5.5 Gesture Interaction

A gesture recognition technique establishes a simple HCI by recognising a users' body movement or postured gestures (Chowdary, Babu, Subbareddy, Reddy, et al., 2014). In Section 4.9, an explanation of the human gesture was given. A human-computer interface which enables the HCI by using a human gesture can pursue a wide variety of approaches and techniques. For instance, the first generation of gesture recognisers was used in Space-War game on DEC PDP-1 and Atari 2600, commonly introduced to market as joysticks. To provide input a system using these devices, a user was required to posture a specific wrist-based gesture to control game plays (Cummings, 2007). Nowadays, by the evolution of gesture recognition techniques, some finger gestures such as double tap, long press, scroll and pinch on a touch-screen display are the HCI techniques commonly preferred and accepted by society. This section, in order to restrict the discussion upon this topic, discusses only some of the modern gesture-recognition techniques and tools in the following sub-sections.

5.5.1 Image Processing

An image-processing technique is a vision-based technique which receives signals formed by an image, a series of images, or a video which are combined by a series of sequential images (known as a video frame), as the input. This processes the signals and publishes patterns which express a specific behaviour in the signals. These images can be provided by an image-capturing device such as a camera or motion-sensing device. The processing signals would be performed by using mathematical operations and the output would be either an image or specific information related to a specific characteristic of the image (Gonzalez and Woods, 2008).

Because of the growth of computer systems, image-capturing techniques, AR and VR power, image-processing techniques became more popular than before and have been applied to a greater variety of applications. Figure 5-15 presents Microsoft

Kinect which is a motion-sensing device which processes the image of a user by using built-in cameras and infrared light projectors. Figure 5-16 presents an image recognition app which recognises each individual finger of the left hand of the user. Figure 5-17 depicts an SSI (Section 4.9.3) which processes a video received from a camera located opposite the user's mouth. Image recogniser software enables speech recognition by reading the movement of lips and classifying data extracted from these movements. Figure 5-18 represents an application of image processing and face gesture recognition which identifies the user's emotions (EPFL, 2016).

Figure 5-15: Gesture recognition by Microsoft Kinect (Cardinal, 2013).

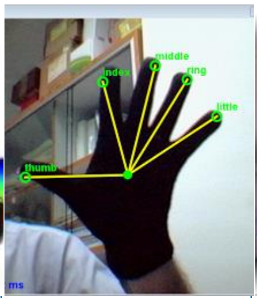


Figure 5-16: Recognising a left hand and fingers by a camera (Attila, 2016).

Figure 5-17: An SSI to recognise speech by reading lips (Denby, Schultz, Honda, Hueber, et al., 2010).

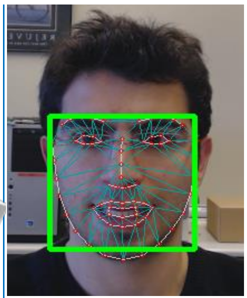


Figure 5-18: Emotion recognition (EPFL, 2016).

5.5.2 Motion and Orientation Sensors

Motion and orientation sensors are used to capture body movement or a specific gesture. This type of gesture recognition measures some aspects of a gesture by providing information collected from different sensors. A Six Degrees of Freedom (6-DoF) refers to the freedom of movement of a rigid body in three-dimensional space (Figure 5-19 presents movements within this space). It specifically occurs when the body is free to change position; forward/backward (surge), up/down (heave), left/right (sway) (as is depicted in Figure 5-20) in three perpendicular axes, in addition to the changes in orientation upon these axes which are most often termed as pitch, yaw, and a roll (Wikipedia, 2016b).

The following list briefly describes some motion and orientation sensors adopted from a list of various sensors and sensor types in Wikipedia (2016a):

1. ***Accelerometer:*** *Measures acceleration forces on X-, Y- and Z-axis* (Figure 5-21). *These forces can be static, when the constant force of gravity is pulling an object the sensor is connected to, or be dynamic, when the sensor moves or vibrates* (Dimension Engineering, 2016).

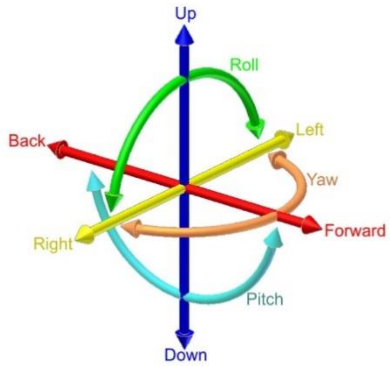


Figure 5-19: 6-DoF of movement in 3 dimensional space (Wikipedia, 2016b).

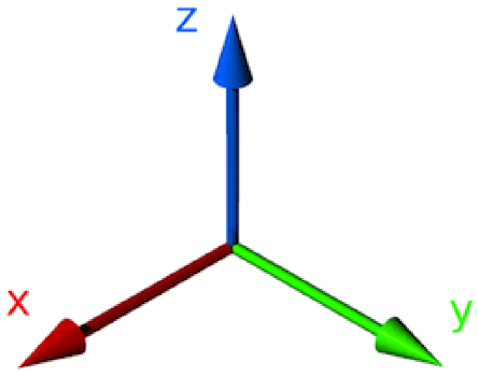


Figure 5-20: Movement over X-, Y- and Z-axes (Wikipedia, 2015b).

2. ***Gyroscope:*** Senses and measures the pitch, yaw and roll around all 3 axes. It also can measure an object's tilt or rotation in a specific direction as is shown in Figure 5-22 (gyroscope chip model L3G 4200D from ST Microelectronics). Unlike the axes names used for accelerometers the three rotation motions are called Yaw, Pitch and Roll (Elrayes Campaign, 2016).
3. ***Compass:*** Presents the four cardinal directions (Figure 5-23) by pointing towards the Earth's magnetic fields (North and South). This can expose an object's movements based on which cardinal direction it points toward.
4. ***Proximity Sensor:*** As is depicted in Figure 5-24, the sensor detects the presence of nearby objects without any physical contact by measuring the reflection of a transmitted infrared light from the object (Yong and Tamara, 2009). This sensor is sometimes combined with devices such as Microsoft Kinect which applies an image processing technique to recognise a movement.
5. ***Bend:*** A Bend Sensor, as is shown in Figure 5-25 is a thin film, sensor strip that indicates the degree of bend forced upon it. Bend sensors are commonly referred to as Flex Sensors (SPI, 2016).
6. ***Micro-Electro-Mechanical System (MEMS):*** With the growth of sensory and molecular Nano technologies, MEMSs are devices compromising a combination of different sensors with the aim of providing more valuable detailed information regarding to an object's motion and orientation. An MEMS device generally ranges in size from 20 micrometres to one millimetre. For instance, Figure 5-26 presents an Inertial Measurement Unit (IMU) device which combines an accelerometer, gyroscope and a magnetometer. This IMU is able to detect an object's specific force, angular rate, and the magnetic field surrounding it.

7. ***Radar-Based Sensor (Soli):*** Google, (2016b) recently introduced a chip which detects the presence and movement of nearby objects without any physical contact. Similar to radar technology, this technique enables a chip to recognise any gesture by transmitting a radio wave towards a target and then, the receiver in the chip intercepts the reflected energy from that target as the Figure 5-27 represents this process. Google has unveiled the project Soli only to introduce the technology, hence, there is still no report regarding its hardware, API, release date, applications and the price.

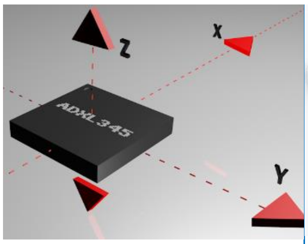


Figure 5-21: A digital accelerometer chip (Engineering 360, 2015).

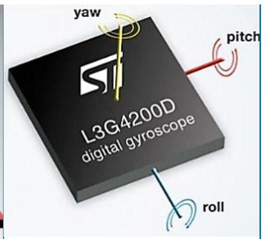


Figure 5-22: A digital gyroscope chip (Marsh, 2016).

Figure 5-23: The four cardinal directions (Anne Kennedy, 2016).

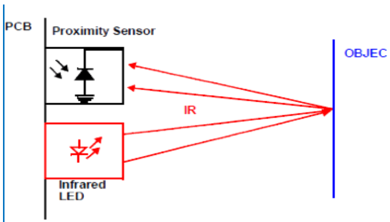


Figure 5-24: Sensing an object within a proximity-detection area (Yong and Tamara, 2009).

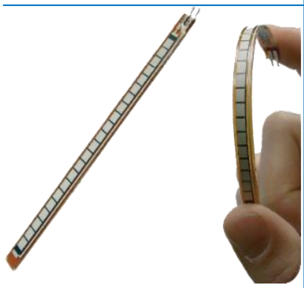


Figure 5-25: A bend sensor (Tactical Marcomms, 2016).

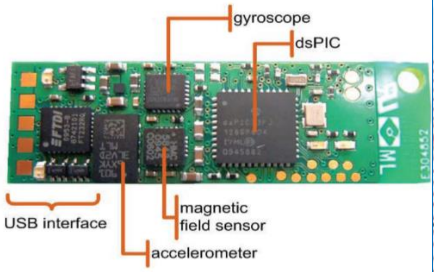


Figure 5-26: An Inertial Measurement Unit chip which combined a gyroscope, accelerometer and magnetiser (Wikipedia, 2016b).

Figure 5-27: Soli project, radar-based gesture detection (Google, 2016b).

The human-computer interface designers, purposefully, combine these sensors in a solution to customise it for a specific application. These solutions, in order to be applied to a real-world application by normal users, require the incorporation of a user-centred software and hardware design. Therefore, Table 5-1 presents some modern gesture recognition devices which are available on the market (A-on-M) currently (Tap and Gest will be available commercially by the beginning of 2017).

Table 5-1: Introduced and available gesture detectors on the market.

A-on-M	*Device Name*	*Gesture Recognition*
Available	***Leap Motion*** **Sensor**: Proximity **Connection**: USB cable	Is a small USB device which is designed to be placed on a physical desktop, facing upward. By using two monochromatic IR cameras and three infrared LEDs, the device observes a roughly hemispherical area, only to a distance of about 1 metre. The LEDs generate pattern-less IR light (Weichert, Bachmann, Rudak and Fisseler, 2013) (Figure 5-28).
Available	***AcceleGlove*** **Sensor**: Accelerometer **Connection**: USB cable	Detects each individual finger movement and is able to track the arm's movement by applying an optional component. It is also equipped with a circuit board which transmits the sensors data into a computer (Meta Motion, 2016) (Figure 5-29).
Available	***CyberGlove*** **Sensor**: Bend and Gyroscope **Connection**: USB cable or Bluetooth	Detects the orientation of the hand, fingers and wrist (6-DoF) (Meta Motion, 2016) (Figure 5-30).
Available	***MYO Armband*** **Sensor**: MEMS, (IMU) **Connection**: Bluetooth	Detects the 6-DoF of the forearm (Lake, Bailey and Grant, 2015) (Figure 5-31).
Available	***Muse Headband*** **Sensor**: Accelerometer **Connection**: Bluetooth	The headband is equipped with two 3-axis accelerometers located behind the ears. This enables the device to detect the user's neck and head movement (Interaxon, 2016) (Figure 5-32).
Dec/2016	***Tap*** **Sensor**: No Report **Connection**: Bluetooth	According to the company, Tap accurately detects any combination of finger touches on any surface and senses a hand's position in a 3 dimensional space (Tap Systems Inc., 2016) (Figure 5-33).
Nov/2016	***Gest*** **Sensor**: MEMS **Connection**: Bluetooth	Detects 6-DoF of the user's wrist and fingers as it is equipped with four IMUs attached to each individual finger, and a fifth IMU for the palm (Gest Co., 2016) (Figure 5-34)

Figure 5-28: Leap Motion (Leap Motion, 2016).

Figure 5-29: AcceleGlove (Meta Motion, 2016).

Figure 5-30: CyberGlove (Meta Motion, 2016).

Figure 5-31: MYO Armband (Thalmic Labs, 2015).

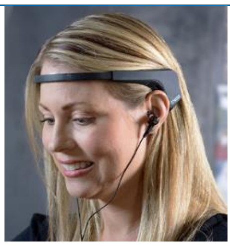


Figure 5-32: Muse headband (Interaxon, 2016).

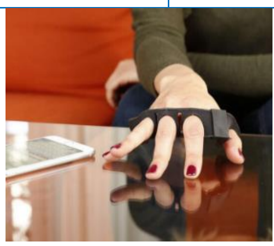


Figure 5-33: Tap (Tap Systems Inc., 2016).

Figure 5-34: Gest (Gest Co., 2016).

As will be explained in detail in Chapter 6, a MYO Armband will be selected and used in the design of the solution that this research study will offer to the existing problem in input provision to a WMS (as was identified in Section 1.2). However, although the MYO Armband is introduced as a device which can detect motion and orientation, it is also capable of sensing the activities of motor neurons in the forearm of users, as will be explained in Section 5.7.1.

5.6 Direct Neural Interaction

As was explained in Section 4.3.2, a specific intercommunication of a group of neurons generates a specific oscillatory activity. The term biomedical signal (bio-signal) refers to the oscillation activities measured and monitored by a sensor and a device. In recent years, the application of bio-signals in HCI system designs has become more popular and is being improved as this enables a direct interaction with a computer system by detecting a specific biological behaviour across a biological body. The increasing diversity of bio-sensing and wearable technologies on the market today has allowed researchers to design more efficient and effective and fully natural User-Interface (UI)s such as an MCI and a BCI.

Through research, the potential of BCI and MCI as commonly approved interaction tools, has been identified. They still, however, have a long way to go to meet a normal user's expectations of an easy-to-use HCI tool. However, they have been used for various purposes, such as controlling wheelchairs, piloting drones, providing alphanumeric inputs and improving the performance of athletes.

As will be discussed in the following sub-sections, the design and development of an HCI system using bio-signals in order to classify and recognise a specific biological behaviour, necessarily must pursue the following sequence of procedures:

1. Bio-signals acquisition using a bio-sensor (commonly known as an electrode) (Section 5.7).
2. Pre-processing the bio-signals in order to extract precise features from which a specific biological behaviour would be emphasised (Section 5.8).
3. Applying a Machine Learning (ML) technique in order to establish the HCI (Section 5.9). Hereby, computer software learns to classify patterns in biological behaviour from the features.

5.7 Bio-Signal Acquisition

A bio-signal can be acquired and measured by employing a variety of sensors and techniques. While designing an HCI system, this method is dependent on specific requirements in the application domain, which determine the type of sensor and technique which has to be employed to achieve an effective and efficient design. The bio-signals can be captured by an invasive or non-invasive electrode. An invasive electrode is often implanted inside the tissue, while a non-invasive electrode needs only to be placed on the surface of skin which is close to a target muscle tissue. Implanting an invasive electrode presents greater risk to the user, since it requires surgery. Therefore, it is applied within a health-care facility.

5.7.1 Applications and Bio-Signal Acquisition for a Muscle-Computer Interface

A Muscle-Computer Interface (MCI) establishes the HCI in real time by interpreting the bio-signals which are acquired by EMG sensors from the motor-neuron activities within a muscle tissue (the EMG technique was introduced in Section 4.9). Applying the EMG sensors is more commonly reported and used in the design of an MCI, however, Bansal, Khan and Salhan (2009) have used an Electrocardiography (ECG) sensor (the sensor basically senses the electrical activity of the heart over a period of time) in a wearable located near the user’s heart. This wearable is able to transmit the user’s heart beat rate into computer software (Alves and Chau, 2010). Alves and Chau (2010) also designed and tested an on/off switch using a Mechanomyogram sensor which can be controlled by small eyebrow movements.

5.7.1.1 EMG Electrodes

Figure 5-35 represents an invasive EMG electrode which basically is a needle that is implanted into a muscle tissue. The electrode is then able to sense a muscular polarisation or depolarisation in the electrode’s neighbourhood (ASET, 1997). Figure 5-36 represents a surface EMG electrode which is attached to the surface of a user’s face skin, near the target muscles to detect generated bio-signals.

Some other applications of an MCI were discussed in Section 4.9.2 to control a robot arm (Backyard Brains, 2016) and in Section 4.9.3 when the researcher designed and developed an SSI using the EMG sensors on the user’s face (Wand and Schultz, 2011).

Figure 5-35: Invasive EMG electrode (Monarch Diagnostic Services Inc., 2016).

Figure 5-36: Surface EMG electrode as a non-invasive technique (InterACT, 2015).

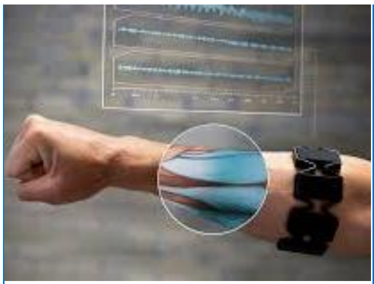


Figure 5-37: MYO Armband (Thalmic Labs, 2015).

Figure 5-38: Prosthetic arm controlled by a MYO armband (Thalmic Labs, 2015).

5.7.1.2 MYO Armband

Using non-invasive or even invasive electrodes has increased the popularity of MCIs over other HCI tools. Thalmic Lab introduced the MYO Armband (Figure 5-31) to the market in March 2015 as the first and only muscle, motion and orientation sensing device on market which has a user-friendly design (Figure 5-37). Table 5-2 presents the specifications of the MYO Armband (Lake, Bailey and Grant, 2015).

The armband (Table 5-2) is equipped with internal software which classifies the wrist gestures introduced and depicted in the above table and provides filtered and processed signals from EMG electrodes and other built in sensors. In addition, there is a variety of open-source API libraries available in different computer programming languages that reduces the amount of effort during the development phase (Goodine, 2016).

Table 5-2: Technical specifications of a MYO Armband.

Arm size	**Expandable between 7.5 - 13 inches (19 - 34 cm) forearm circumference.**	***Sensors***	**Eight medical grade stainless steel EMG sensors which streams 8-bit data at a Sample Rate (SRate) of 200 *Hz*. Nine-axis IMU (data is streamed at 50 *Hz*).**
Weight	93 grams.	***Processor***	ARM Cortex M4 Processor.
Thickness	0.45 inches (1.143 centimetres).	***Haptic Feedback***	Short, Medium, Long Vibrations.
Communication	Bluetooth 4.0 low energy smart wireless technology.	***Power***	Micro-USB charging (Built-in rechargeable lithium ion battery. It holds one full day use out of single charge.
Gestures and Motion	6-DoF of the forearm (captured by IMU). Gestures: double tap, fist, fingers spread, wave in and wave out. 		
Compatible OS	WINDOWS, MAC, Linux, iOS and Android.		

The MYO Armband is generally known as a successful HCI device as the number of its applications is increasing in fields such as gaming, entertainment, controlling a machine (such as robots, gadgets and drones), media, sport and health care since the time it was released (Thalmic Labs, 2015). For example, as was represented in Figure 5-38, an amputee user can control a prosthetic arm as the armband can detect the potential muscular activity in the arm (Mattioli, Lamounier, Cardoso, Soares, et al., 2011).

5.7.2 Applications and Bio-Signal Acquisition for a Brain-Computer Interface

An Electroencephalogram (EEG) is able to capture the bio-signals generated by neural network activities in the human brain by picking up electrical impulses from the scalp using EEG electrodes (Section 4.3.2). In order to depict an EEG electrode, Figure 5-39 represents a series of EEG electrodes on the surface of user's scalp and Figure 5-40 depicts an X-ray picture which represents an implanted array of EEG electrodes upon the brain tissue just under the scalp. The applications of data from an fMRI (Section 4.4.2) are frequently reported in the literature as a method to acquire bio-signals from the human brain for a BCI as well.

Figure 5-39: Non-invasive surface EEG electrode (Davies, 2015).

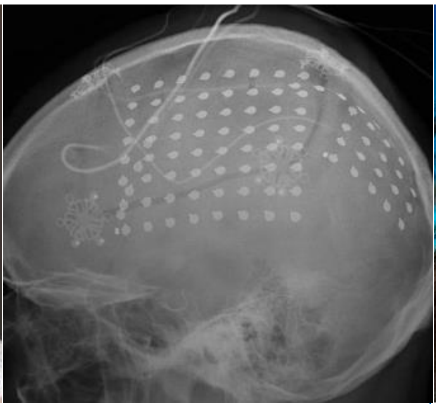


Figure 5-40: An X-ray picture of the placement of invasive EEG electrodes over the scalp (Epilepsy Center, 2016).

Figure 5-41: Neurosky Mindwave, brain sensing headband (NeuroSky, 2016).

Figure 5-41 represents Neurosky which is a commercial brain sensing device available on the market which has been used as a BCI in different application domains. There is also the Muse Headband from Interaxon Company which was shown in Figure 5-32. The Neurosky covers the forehead with only one electrode placed on FP1 where the Muse Headband covers the user's forehead on areas FP1 and FP2 with five EEG electrodes. In addition, two other electrodes are located behind each ear, placed on TP9, and TP10. However, the BCIs which use devices available on the market have a long way to go to meet a normal user's expectations of an easy-to-use HCI tool. The current BCIs have not extended their capabilities further than measuring the user's concentration, specific feelings, emotions and some states of mind.

Chapter 4 presented an overview of some brain-computer interfacing techniques and applications in Sections 4.4.2 and 4.6.2 where the discussion on these techniques was expanded using the visual and sound stimuli. In Section 4.7 an application of a BCI was introduced where the system was able to measure human concentration while performing a specific task. Lim, Lee, Guan, Fung, et al. (2012) have trained and enhanced attention in order to treat Attention Deficit Hyperactivity Disorder via a BCI system which provides a neural feedback to the user.

The companies producing Muse and Neurosky headbands have provided a Software Development Kit (SDK) which includes appropriate API for measuring a user's concentration as well as some other feelings. This could reduce the complexity of recognising patterns which express biological behaviours in the human brain caused by feelings and states of mind.

5.8 Signal Processing and Feature Extraction

Most motion, orientation and bio-sensing sensors construct a continuous sequence of numbers upon a time axis. In order to depict this type of data, Figure 5-42 presents the raw EMG time-series data captured by a MYO Armband from one of its eight electrodes (Electrode number 4) within 1.43 seconds of the user pressing the ring finger on a surface. The data is recorded by the SRate of 40 Hertz (*Hz*) which means the armband produces time-series data in 25 millisecond (*ms*) time intervals.

The term Knowledge Discovery, refers to the broad process of finding knowledge in data, and emphasises the high-level application of particular data-mining methods. It is of interest to researchers in machine learning, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition for expert systems, and data visualization (Fayyad, Piatetsky-Shapiro, Smyth and Uthurusamy, 1996, p. 1). The main reason that bio-signals have to be pre-processed is to increase the efficiency of Knowledge Discovery by improving data quality and removing or reducing the noise present in the data.

According to Moura (2009), Arief, Sulistijono and Ardiansyah (2015), the term Signal Processing refers to the use of mathematical, statistical and computational techniques in order to smooth, minimise or remove noise in a dataset. These filtering techniques aim at minimising the complexity of data to facilitate the discovery of precise knowledge from a dataset. For instance, Figure 5-43 depicts the processed signal in Figure 5-42 by a normalisation technique (Section 6.5.2.1). Section 6.5.2 will present some data-smoothing techniques which are regularly applied and reported in filtering bio-signal data and are used in designing the artefact this research study will offer.

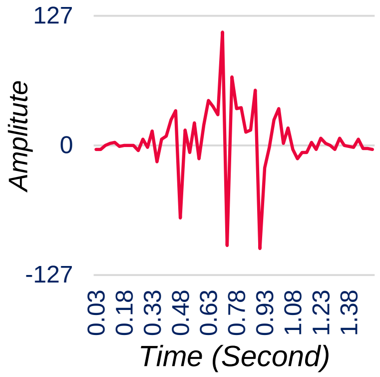


Figure 5-42: The raw EMG time series signal captured by MYO Armband (SRate of 40 *Hz*).

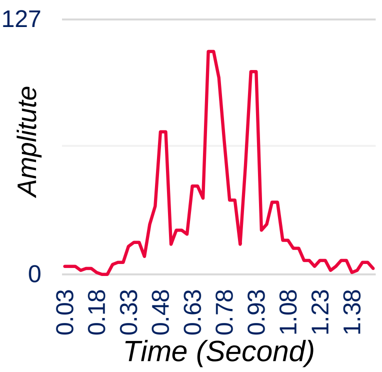


Figure 5-43: Noiseless and processed data.

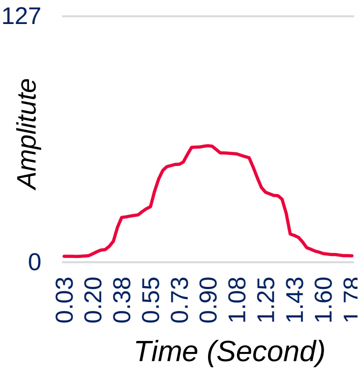


Figure 5-44: A feature extracted from raw data.

Useful and precise knowledge from a dataset of bio-signals can explicate a decisive pattern for different specific biological behaviours in the dataset. In a biological behaviour recognition system, after the pre-processing phase, Feature Extraction would be done. Feature Extraction is basically related to the reduction of the dimensionality of data since it forms decisive features (for instance, Figure 5-44 presents a feature extracted from the signal which is depicted in Figure 5-43) which can facilitate the ML process (Fayyad, et al., 1996). Section 6.5.3 will introduce some popular Feature Extraction techniques which are regularly applied to the development of different direct neural interfaces.

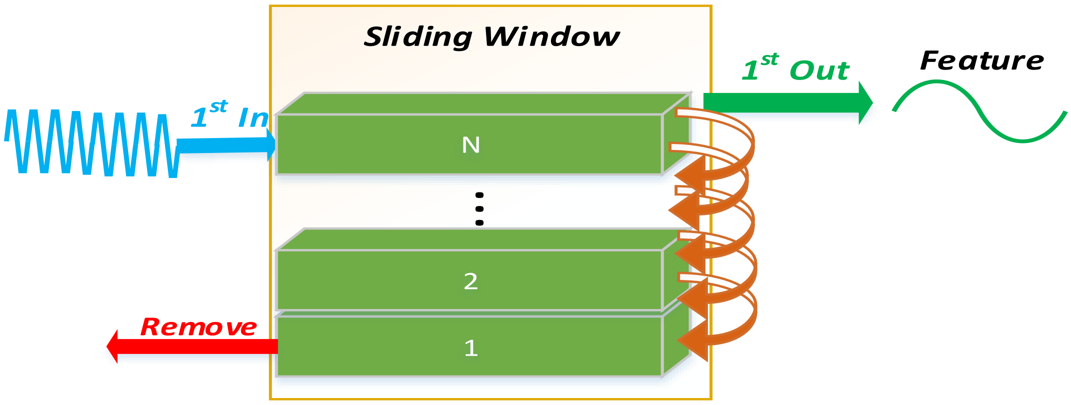


Figure 5-45: The structure of the sliding window.

Signal Processing and Feature Extraction techniques expose some data which sometimes can even be plotted to be understandable by humans. This necessarily requires techniques to be applied to a dataset which contains a part of the data flow. As is depicted in Figure 5-45, a Sliding Window receives a signal at the input and holds a fixed number of previously detected signal values inside itself to enable applying Signal Processing and Feature Extraction techniques upon data it holds inside. The output of the Sliding Window is a smoothed value of data expressing different features at the time (Vafaeipour, Rahbari, Rosen, Fazelpour, et al., 2014).

5.9 Machine Learning for Classifying Bio-Signals

The extracted features are used as the input data for a Machine Learning (ML) technique. ML is an Artificial Intelligence (AI) technique which enables a system to learn from different paradigms (Saponas, et al., 2009). Pattern recognition is a technique used in ML that emphasises the recognition of specific patterns and symmetries in data (Bishop, 2006). Pattern recognition techniques can pursue either a supervised learning approach when labelled data is available or an unsupervised learning approach when no labelled data is available and the algorithms are used to recognise previously unknown patterns (Mohri, Rostamizadeh and Talwalkar, 2012). Data classification is a popular technique in pattern recognition which, as its name implies, discovers useful knowledge by classifying and labelling data. This technique is able to label and classify specific behaviours of bio-signals in specific features (Coelhoa and Limab, 2014).

Georgoulas, Chudacek, Rieger, Stylios, et al. (2005) discuss and suggest some techniques for data classification such as using Support Vector Machine, Decision Trees and K-Neural Networks, which can be applied to the classification of bio-signals (Saponas, et al., 2009; Wua, Maob, Weic, Fua, et al., 2016). Different types of Artificial Neural Network (ANN)s are also frequently reported by other researchers as successful and powerful data classifiers in this type of data classification (Abbaspoura, Fallah, Lindena and Gholamhosseini, 2016; Ardestani, Chen, Wang, Lian, et al., 2014; Ardestani, Zhang, Wang, Lian, et al., 2014; Hua, Wanga, Wub, Duc, et al., 2015; Valbuena, Teymourian, Volosyak and Graser, 2010).

5.10 Conclusions

This chapter aimed to iterate the Rigor Cycle in the DSR methodology where a research study constructs a knowledge base which can assist to improve the designing of an artefact within the Design Cycle. Therefore, the chapter introduced some available interaction methods and techniques as well as some popular HCI devices which can be used to design a solution to the problem by using sensory technologies. In addition, the chapter introduced some techniques and procedures which can be used in the development of an IT-based artefact using biological sensory technologies. Consequently, this chapter was answering the research question 3 (*What are the latest sensory technologies which can improve the Human-Computer Interaction within the problem domain?*) and research question 4 (*How can a sensory solution improve the current interaction techniques?)* to achieve the main and secondary objectives of this research study.

From a human-centred perspective, as is modelled in Figure 5-46, interaction techniques are divided into two general categories where a technique can enable a user to provide inputs to a computer and/or enable the computer to provide feedback to the user. Providing feedback from the computer to the user can be achieved by sensors generating light wave and soundwave generator sensors to establish an interaction path with the user by using human visual and auditory perception abilities. Technologies enable a computer to receive inputs from a user by sensing various behaviours of the user and translating each into an understandable command. Technology enables a human’s movements, speech and behaviours to be perceived from neural activities.

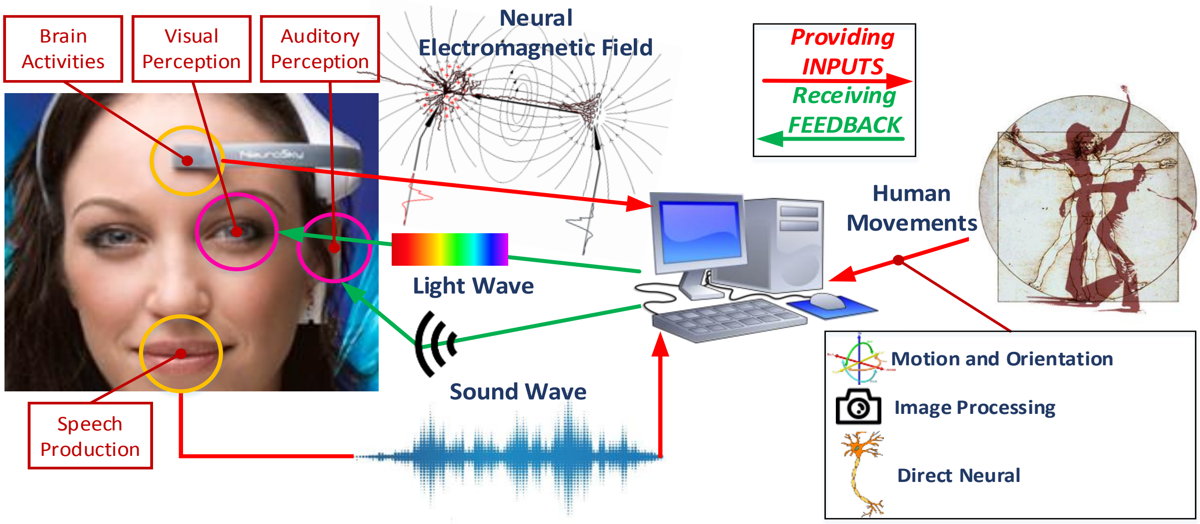


Figure 5-46: A human-centred model for the HCI.

Table 5-3 presents some popular HCI techniques including traditional displays (TD – Section 5.2.1), Virtual Reality (VR – Section 5.2.2), Augmented Reality (AR – Section 5.2.3), image processing based gesture interaction (GRI – Section 5.5.1), gesture interaction using motion and orientation sensors (GRS – Section 5.5.2), as well as direct neural interaction technologies (Section 5.6) such as a BCI and an MCI. While offering a solution to solve the main problem (Section 1.2), an appropriate combination of these techniques would influence the effectiveness and efficiency of the solution. The table also expresses some criteria which reveal the degree of automation in HCI of each technique when the following are established; visual interaction (V-I – Section 5.2), auditory interaction (A-I – Section 5.4), verbal interaction (Ve-I – Section 5.3), gesture interaction (G-R – Section 5.5) where the user is able to perform a task in a noisy environment (W-i-N), and eyes-free (E-F) and hands-free (H-F). In addition, the table indicates if a technique assists the user with the degree of his/her concentration while performing a task (A-H-C).

Table 5-3: Capabilities of some HCI techniques in interaction.

Technique	*V-I*	*A-I*	*Ve-I*	*G-R*	*W-i-N*	*E-F*	*H-F*	*A-H-C*
TD	✓	✗	✗	✗	✗	✗	✗	✗
AR	✓	✗	✗	✗	✗	✓	✓	✗
VR	✓	✗	✗	✗	✗	✗	✓	✗
Voice Headsets	✗	✓	✓	✗	✓	✓	✓	✗
GRI	✗	✗	✓	✓	✓	✓	✓	✗
GRS	✗	✗	✗	✓	✓	✓	✓	✗
MCI	✗	✗	✓	✓	✓	✓	✓	✗
BCI	✓	✓	✓	✓	✓	✓	✓	✓

TD, AR and voice headsets were introduced as the most popular techniques employed in the interaction with a WMS in Section 3.7 when they were compared based on the degree of automation they release. While comparing these techniques to each other, the AR was introduced as the most efficient and effective technique since the modern Smart-Glasses used in AR are equipped with other sensors such as a microphone, camera, motion and orientation sensors which enable a device to establish a more efficient HCI. Table 5-3 introduced the BCI as the most acceptable interaction technique, however, as was pointed in Section 5.7.2 this technique is still far from the users' expectations of a user-friendly system.

The chapter also introduced some popular devices for HCI which take advantage of these techniques. These devices can be combined together to improve and facilitate the HCI when they enable different methods of interaction. For instance, Table 5-4 presents some popular portable devices available on the market which allow a hands-free and eyes-free interaction. These devices can be combined or even directly used in a solution to solve the existing problem in interaction with a WMS.

Table 5-4: Capabilities of some HCI devices in interaction.

Device	*V-I*	*A-I*	*Ve-I*	*G-R*	*W-i-N*	*A-H-C*
CyberGlove	✘	✘	✘	✓	✓	✘
MYO Armband	✘	✘	✘	✓	✓	✘
Google Glass	✓	✓	✓	✓	✘	✘
Neurosky Headband	✘	✘	✘	✘	✓	✓

As can be observed in the Table 5-4, however, Google Glass are presented as a technology which can recognise gestures and receive inputs verbally, it processes the images of the gestures captured by its built-in camera but cannot decipher the speech in noisy environments. Therefore, the gesture-recognition capability of the device would be limited to the detection of gestures and movements which are placed directly opposite its camera. Therefore, it is better to combine Google Glass with a MYO Armband and CyberGlove as well as a Neurosky Headband to improve interaction in noisy environment while assisting the user in the degree of his/her concentration on a task.

Other techniques, technologies and devices which would be available on the market in the near future were introduced in this chapter as well. For instance, a combination of Cyber Display (Section 5.2.3) and Whisper Chip (Section 5.3) in the production of future Smart-Glasses can improve the applications of this technology in the AR and enable this device to work even in noisy environments. The Microsoft HoloLens (Section 5.3.4) can also influence visual interaction positively by improving the visual information which a user would explore.

During discussions in Sections 5.7, 5.8 and 5.9, the procedures involved in the design and development of a sensory HCI system, specifically a neural based HCI (Section 5.7) were described. In summary, the development of a sensory HCI first, requires, acquiring signals (Section 5.7) by using a sensor, processing the signals and then extracting features (Section 5.8) with the aim of exposing a specific behaviour in the bio-signals. Finally, by using an ML technique (Section 5.9) a neural based HCI can be established. These procedures will be pursued in the next chapter, Chapter 6 when the research study designs and develops a primary prototype for the selected solution.

Chapter 6. Design and Evaluation of the Solution

Objective(s) of Chapter

1. *Prototyping a solution using a selected sensory technology.*
2. *Acquiring a more specific knowledge-based with regard to design and development of the prototype.*
3. *Implementing and training an ANN to classify the gestures within the prototype.*
4. *Designing an experimentation to evaluate the prototype.*
5. *Analysing the results of the evaluation.*

Structural Overview of the Chapter

Chapter 1: Introduction
Chapter 2: Research Design
Chapter 3: Warehouse Management and Automation Technologies
Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems
Chapter 5: Sensory Technologies for Human-Computer Interaction

Chapter 6: Design and Evaluation of the Solution

6.1 Introduction
6.2 Design of the Proposed Solution
6.3 Human Factors Involved in Designing the Prototype
6.4 Non-Stationary State of Bio-Signals
6.5 Signal Processing and Feature Extraction Techniques
    6.5.1 Gesture Selection
    6.5.2 Data Reduction and Smoothing → 6.5.2.1 Min-Max Scaling Normalisation; 6.5.2.2 Polynomial Curve Fitting
    6.5.3 Feature Extraction → 6.5.3.1 Sliding Root Mean Square; 6.5.3.2 Wavelength; 6.5.3.3 Correlative Feature: Discrete Convolution
6.6 Artificial Neural Networks
    6.6.1 The Artificial Neuron
    6.6.2 The Artificial Neural Network Topologies
    6.6.3 The Backward Propagation of Errors Learning Algorithm
    6.6.4 The Resilient Back Propagation Learning Algorithm
6.7 Architecture of the Prototype
    6.7.1 EMG Service Provider Unit
    6.7.2 Signal Processing Unit
    6.7.3 Machine Learning Unit
    6.7.4 User-Interface
    6.7.5 Report Generating Unit
6.8 Experimentation
    6.8.1 Participants Recruitment
    6.8.2 Setup
    6.8.3 Experimentation-1
    6.8.4 Experimentation-2
6.9 Evaluation Experiment and Analysis Results
    6.9.1 Evaluating the Training-Function for the Artificial Neural Network
    6.9.2 Evaluating the Effects of Signal Processing and Feature Extraction Techniques upon the Performance of the Data Classification
    6.9.3 Evaluating the Accuracy of Gesture Recognition → 6.9.3.1 Evaluating the Gesture Classification; 6.9.3.2 Evaluating the Efficiency of Input Provision
    6.9.4 Evaluating the User Experience
6.10 Conclusions

Chapter 7: Conclusions and Future Research

6.1 Introduction

The discussions and information provided in Chapter 4 and Chapter 5 provided an appropriate knowledge base which can assist this research study with its contribution towards designing a solution to the existing problem in interaction with a WMS (Section 1.2) by using different sensory-based HCI devices (Section 1.3) available on market. Chapter 3 identified the environment in which the problem was occurring by introducing and comparing the popular automation techniques and technologies within this environment. Following the DSR methodology, this chapter specially focuses on the Design Cycle in the DSR methodology which regulates the design, development and evaluation of an IT-based artefact. The aim is to investigate the efficiency and effectiveness of the artefact on solving the existing problem in interaction with a semi-simulated WMS.

The effectiveness and efficiency of the offered artefact will be determined by the degree it enables users to interact with a computerised system such as a WMS, hands-free (Section 4.9.1), eyes-free (Section 5.2.3) and error-free. With respect to the limitations and scope of this research study (as were determined in Section 1.6, Scope and Limitations), the solution offered at this stage will only focus on improving the provision of possible input into a WMS. This takes place by employing a gesture recogniser device commercially available on the market, and ignoring the reduction of human-caused errors (Section 4.7.2) and eyes-free interaction. Therefore, in order to design a solution for the problem, this chapter will motivate and discuss the design (Section 6.2) and development of a proposed Muscle-Computer Interface (MCI) prototype (MCIp) which uses EMG signals acquired by a MYO Armband around the user’s forearm to establish HCI.

The MCIp is supposed to classify and recognise finger-based gestures. Therefore, this chapter will iterate the Rigor Cycle (Section 2.3.2) to acquire more knowledge-based information necessary to guide the design and development of the MCIp and to use the bio-signals for the development of the MCIp as it classifies the bio-signals acquired from the forearm of user. Section 6.3 introduces what muscles are engaged within different muscle-groups of the user’s forearm when moving each individual finger. Section 6.5 explains the Signal Processing and Feature Extraction techniques that will be employed in the development. Section 6.5.1 identifies the features of selected gestures, as well as the data-smoothing techniques (Section 6.5.2) applied to the features and Section 6.5.3 explains the process of their extraction.

Section 6.6 describes an ANN and explains the implementation and training of an ANN for the MCIp with the purpose of classifying and labelling the features. Then, Section 6.7 discusses the proposed architecture for the MCIp by explaining different components in the architecture.

Section 6.9 will also explain other evaluations which had to be conducted in order to select an appropriate architecture for the employed ANN in the MCIp (Section 6.9.1) and Signal Processing and Feature Extraction techniques (Section 6.9.2). To evaluate the current design of the MCIp, Section 6.8 will explain the design of experimentation, which in Section 6.9 and in sub-sections 6.9.3 and 6.9.4 are aimed at evaluating the effectiveness and efficiency of the MCIp in a semi-simulated real-world situation.

6.2 Design of the Proposed Solution

As there is still no report in the literature and market regarding a fully-focused solution to the main problem, this research study needs to design and offer a novel solution. A prototype (was defined in Section 2.6) is an elementary working model which can pursue the purposes of a solution. Jones and Rita (2000) introduce the process of designing an efficient and effective solution by using a prototype, involving a number of iterations including design, development and evaluation of the prototype over a cycle in order to develop and enrich the design (Figure 6-1). This iteration can be frozen once the prototype has developed enough to cover all the required features of the solution.

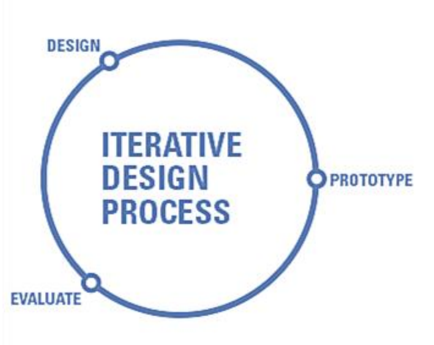


Figure 6-1: Design processes using prototyping (Jones and Rita, 2000).

Figure 6-2: Stages of innovation (Colligan, 2014).

Colligan (2014) introduces the design process as an iteration upon an infinite fractal (Figure 6-2) as the iteration would be initiated over time, when the techniques, technologies and expectations of users grew dramatically and day by day. Consequently, a designer is required to provide innovative solutions to fill gaps in the available systems by employing newer techniques. A portion of this fractal in the design of visual interaction tools in HCI can be observed where this research study explained the evolution of visual interaction techniques in Section 5.2.

As was concluded in Section 5.10 (Table 5-4), a combination of either a MYO Armband, or CyberGlove, with Google Glasses, can enable users to provide inputs to a system by posturing finger-based gestures. Due to time restriction in this research project, investigation of the performance of both devices when applied to a real-world problem was not possible. Therefore, a MYO Armband was purchased from Thalmic Lab in Canada in order to be used in this research project.

With respect to the limitations and scope of this research study (as were determined in Section 1.6, Scope and Limitations), the solution offered at this stage will only focus on improving the provision of input into a WMS. This takes place by employing a gesture recogniser device commercially available on the market, and ignoring the reduction of human-caused errors and eyes-free interaction.

As was introduced in Section 5.5.2, the MYO Armband is capable of recognising motion and the orientation of the user's forearm, however, the current MCIp is only designed with the aim of recognising some gestures which are always available using bio-signals rather than using signals from other built-in sensors (these sensors and the capabilities of the MYO Armband were described in Section 5.7.1.2).

6.3 Human Factors Involved in Designing the Prototype

It was explained in Section 4.9, that a muscle in the muscular system, in response to a spike, performs changes over its length and size. These changes prompt a physiological body movement when a muscle, attached to bones and joints with tendons, is stimulated (Saponas, et al., 2009). In the same way, limbs on the body such as hands, fingers and wrists can be moved to posture a variety of movements. For example, the limbs can be flexed, extended, abducted or circumducted. Each of these movements involves different muscles in different muscle-groups, in different ways. The MYO Armband used in the MCIp fits over the user's forearm and is able to sense activities of muscle-groups within the forearm.

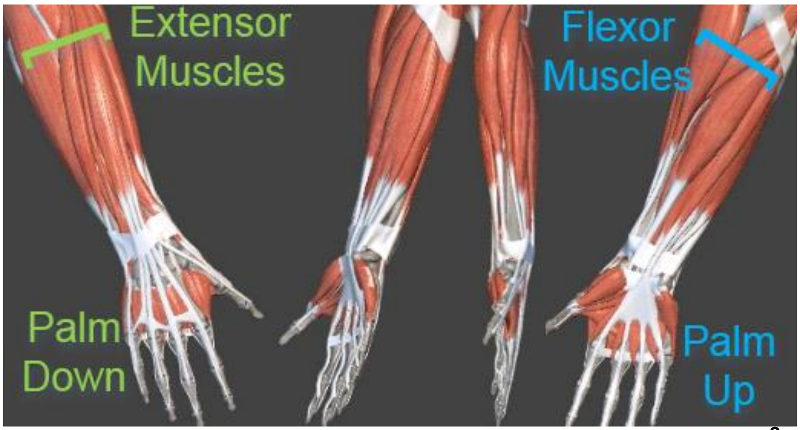


Figure 6-3: The muscles in a human's right-hand forearm[3].

Figure 6-3 represents the composition of muscles, in a human's right hand forearm, which enable the wrist and the fingers of the hand to be moved. By adjusting their length, each tendon connected to the fingers can move. Dr Hal Blumenfeld explained this complicated process in his book (Blumenfeld, 2010). Figure 6-4 filters what Blumenfeld (2016) noted and depicts only the flexion and extension of the hand fingers.

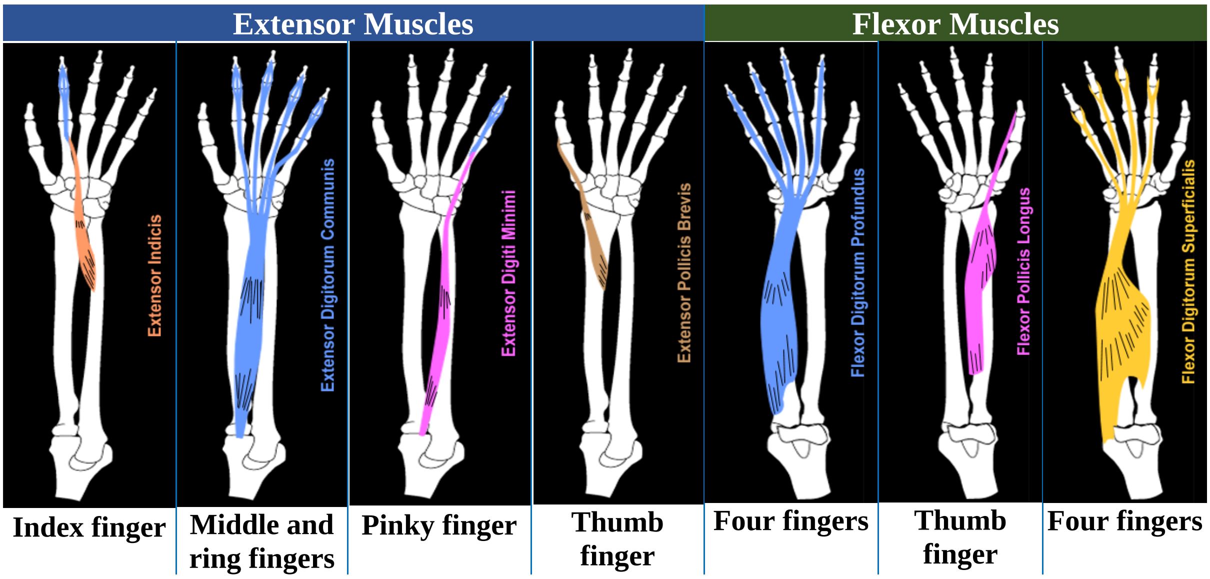


Figure 6-4: The extensor and flexor muscles in a human's right hand and the relative finger movements (KUMC, 2016).

The activities in the muscles become more complex, when for example, a flexion occurs by bending, making a fist, gripping, grasping or folding the fingers. For

[3] Adopted from Visual Anatomy Lite mobile app. Available at: https://itunes.apple.com/za/app/visual-anatomy-lite/id523422151?mt=8 [Accessed June 3, 2016].

instance, the flexion is handled by the flexor muscle group and the extension by the extensor muscle group (Figure 6-3). The muscles within different muscle-groups behave differently depending on each movement style (Blumenfeld, 2010). For instance, as was represented in Figure 6-4, each specific muscle within the extensor and flexor muscle-groups is activated separately to flex or extend one specific finger when the connected tendon to the muscle and finger stretches.

6.4 Non-Stationary State of Bio-Signals

The bio-signal is introduced multiple times in literature as a nonstationary and complex signal since its velocity can be easily impacted by a wide variety of variables. These include the amount of body fat, hair, the size/shape of muscles, the amount of stress on the muscles, age, gender, heart beat pulses and random physical conditions. This makes the signal complex, requiring a great amount of effort to process and interpret (Linnamo, 2002; Machine-learning-team, 2014). For instance as was explained in Section 4.9.1, Linnamo (2002) presented the noise in EMG signals caused by the stress on the forearm and biceps muscles when the subject moves the arms concentrically and eccentrically. McFarland, Sarnacki, Vaughan and Wolpaw (2005) used EMG and ECG electrodes to remove the noise generated by the heartbeat and the movement of facial muscles from the EEG signals captured from the participant’s scalp.

When an MCI is performed in a real-world situation, it has to recognise whether the user is making a gesture, or not. This is essential to prevent inaccuracy in the classification of gestures and increase the accuracy of gesture recognition. Some particular application domains require just-in-time response which might influence the appeal of this interaction technique. Even in application domains that do not require just-in-time response, such as providing alphanumeric inputs, the existence of this limitation results in inaccurate results. This could, for example, occur when the user flexes the middle finger and then shifts to the flexion of the ring finger. There are also other factors causing a non-stationary state of bio-signals. In this case the muscles pass through an intermediate state, which may affect the result of gesture recognition (Saponas, et al., 2009, 2010).

6.5 Signal Processing and Feature Extraction Techniques

The main functionality of the MCIp is to classify and recognise some finger based gestures which a user would posture without difficulty. The proposed gestures would be categorised into two gesture-groups. One would be used to measure the performance of the gesture classifier and the user has to posture them hands-free. The other gesture-group would be used in a real-world application and the user would posture it even when both of his/her hands are busy.

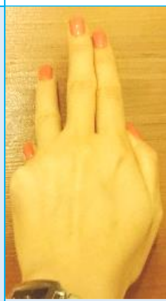
Each gesture generates different bio-signals as it is naturally dependent on specific and unique behaviour in the forearm muscular system. The following sub-sections describe both gesture-groups (Section 6.5.1) while explaining the mathematical, statistical and computational techniques which would be applied to minimise or remove the noise existing in the acquired bio-signals (Section 6.5.2). In addition, the discussion on these techniques will be expanded to other techniques which would be applied to the extraction of a specific feature of a specific gesture (Section 6.5.3).

6.5.1 Gesture Selection

As it is presented in Table 6-1, two gesture-groups were selected, each consisting of five different finger-based gestures, in addition to a relax mode. The gesture-group I consists of four gestures postured by a pinch between the thumb and one of the other fingers and the fifth gesture, is the spreading of five fingers altogether. The user also relaxes the fingers by making a fist without stress in the muscles to form the relax mode (RM). The gestures in this gesture-group must be postured hands-free.

The customised gesture-group II includes applying pressure on a surface for a long time (an approximate amount of 600 *ms*) with the middle, ring, pinky and thumb finger. The index finger gesture would be postured by extending the finger.

Table 6-1: The gestures within each gesture-group (Gesture-group *I*: The left hand of user. Gesture-group *II*: the right wrist of the user).

Gesture -Group	*Relax Mode (RM)*	*Index Finger (IF)*	*Middle Finger (MF)*	*Ring Finger (RF)*	*Pinky Finger (PF)*	*Others*
I						 **Fingers Spread (FS)**
II						 **Thumb Finger (TF)**

6.5.2 Data Reduction and Smoothing

The following sub-sections represent techniques which were applied to reducing and smoothing the disparity and trend of EMG data in the Sliding Window.

6.5.2.1 Min-Max Scaling Normalisation

This technique, in order to reduce the inconsistency in data and to bring all values into a specific range uses the value of x' which is measured by:

$$x' = a + \frac{(x - x_{min})(b - a)}{x_{max} - x_{min}} \tag{6-1}$$

where a and b are arbitrary values to limit the range (Patro and Sahu, 2015).

6.5.2.2 Polynomial Curve Fitting

This function fits a curve on a data series by assuming the data series as a function of $f(x)$ (Kayikcioglu and Aydemir, 2010) where:

$$f(x) = m_0 + \sum_{k=1}^{k=n} m_k \,(x^k) \tag{6-2}$$

In order to fit a curve on a dataset, the function changes the degree of k and finds the best match on the data trend.

6.5.3 Feature Extraction

To reduce the dimensionality of the data and reveal different meaningful features from one series of data, the techniques explained in the following sub-sections are implemented on the MCIp. These techniques also convert raw data into more understandable and relative forms of data.

6.5.3.1 Sliding Root Mean Square

A one-dimensional feature is extracted by measuring the Root Mean Square (RMS) value of the normalised values in the Sliding Window with the size of n (Phinyomark, Phukpattaranont and Limsakul, 2012). The RMS value extracts an envelope from the raw data and is given by:

$$RMS = \sqrt{\frac{\sum_n x_n^2}{n}} \tag{6-3}$$

6.5.3.2 Wavelength

The wavelength (WL) value measures the complexity of the EMG signal (Arief, et al., 2015) and can be calculated by:

$$WL = \sum_{K=1}^{k=n} |x_{k-1} - x_k| \tag{6-4}$$

6.5.3.3 Correlative Feature: Discrete Convolution

In order to reduce the impacts of factors which cause a non-stationary state of the bio-signals (identified in Section 6.4), additional relative features can be extracted, by applying discrete convolution. This implies implementing cross-correlation between individual signals. This generates an $n * n$ triangular matrix of M_{Correl} where n is the number of electrodes. M_{Correl} can be defined as:

$$M_{Correl} = \begin{bmatrix} 1 & x_{E1:E2} & x_{E1:E3} & \cdots & x_{E1:En} \\ & 1 & x_{E2:E3} & \cdots & x_{E2:En} \\ & & 1 & \cdots & \vdots \\ & & & \ddots & x_{En-1:En} \\ & & & & 1 \end{bmatrix} \tag{6-5}$$

The number of features can be extracted by M_{Correl} for n number of electrodes is measured by N where:

$$N = \frac{n^2 - n}{2} \tag{6-6}$$

A discrete convolution is a mathematical way of combining two finite data series of f and g to form a third signal $Conv(x)$ (Chowdhury, Reaz, Ali, Bakar, et al., 2013) and is measured by:

$$Conv(x) = \sum_{k=0}^{k=M} f[k].\, g[x-k] \tag{6-7}$$

where M is the number of data in both f and g. The feature is then extracted from the average value of all of the computed convolution values by:

$$Feature_{Conv(x)} = \frac{1}{M} * \sum_{k=1}^{k=M} Conv(x) \tag{6-8}$$

6.6 Artificial Neural Networks

Basically, Artificial Neural Network (ANN)s are based upon an interpretation of the biological neural network (nervous system) function as was described in Section 4.2.1. Figure 6-5 depicts a simple ANN architecture which consists of a number of small processing units connected to each other each of which is called an artificial neuron or perceptron (as will be identified in Section 6.6.1) within a different number of layers. The neurons are however able to connect and communicate with other neurons, constructing, destructing, and strengthening these connections during a learning process (as will be discussed in Sections 6.6.3 and 6.6.4). The ANN models a biological spike by an activation function. The artificial neuron receives inputs from cells in its neighbourhood through connections that are weighted. The activation function in the artificial neuron fires a perceptron when it is assigned with a value within a specific range (Mehrotra Mohan and Ranka, 1997).

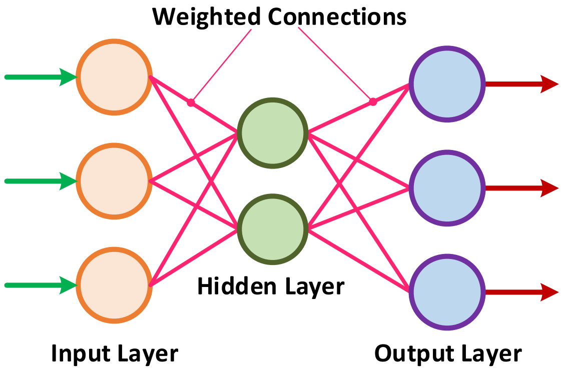


Figure 6-5: A simplified Artificial Neural Network with multiple layer interconnection between neurons.

ANNs can differ from each other by the activation function of a neuron (Section 6.6.1), the composition of the connections between the neurons in different layers which is also known as ANN topology (Section 6.6.2) and while modelling the network, the learning paradigm that modifies the weights of the connections (Section 6.6.3). The following sub-sections describe these components and the topology of ANN which will be later used in the development of the MCIp.

6.6.1 The Artificial Neuron

According to Priddy and Keller (2005), an artificial neuron receives a vector of inputs (Figure 6-6):

$$\vec{I} = [x_1, x_2, x_3, \cdots, x_i] \tag{6-9}$$

from a vector of associated weighted connections of

$$\vec{\mathrm{W}} = [\mathrm{w}_1, \mathrm{w}_2, \mathrm{w}_3, \cdots, \mathrm{w}_\mathrm{i}] \tag{6-10}$$

The net value of a neuron is calculated by the summation function of S where:

$$S = \sum_i w_i x_i \tag{6-11}$$

As the output, the neuron fires the value of O which is known as the threshold rate of the neuron. A neuron fires the value O, as the equal as net value S, if the network connects neurons in different layers to each other linearly. Otherwise, the neuron determines the threshold rate of O by passing the S value through an activation function of f.

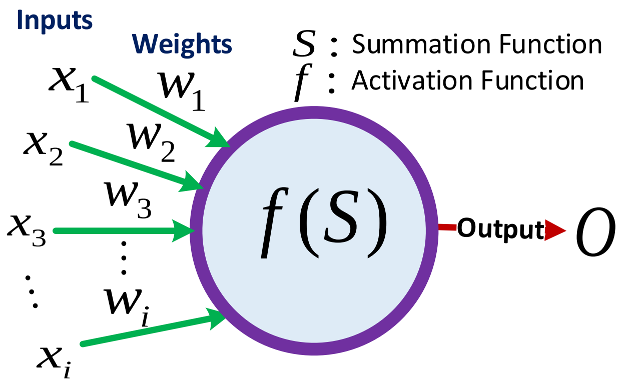


Figure 6-6: A model of an artificial neuron.

For instance, Figure 6-7 presents when a Sigmoid activation function of $\sigma(S)$ fires the threshold rate of O for the summation function of S (Equation 6-11) in the range between $[0, 1]$, by the formula:

$$O = \sigma(S) = \frac{1}{1 + e^{-S}} \tag{6-12}$$

The partial derivative of the Sigmoid function with respect to its argument, S, can be shown by (Wagstaff, 2008):

$$\frac{\partial \sigma(S)}{\partial S} = \sigma(S)(1 - \sigma(S)) \tag{6-13}$$

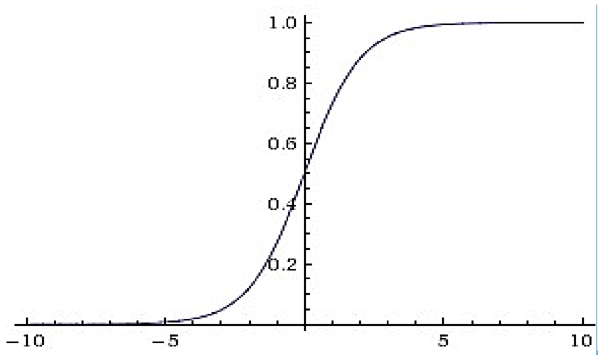


Figure 6-7: Sigmoid activation function.

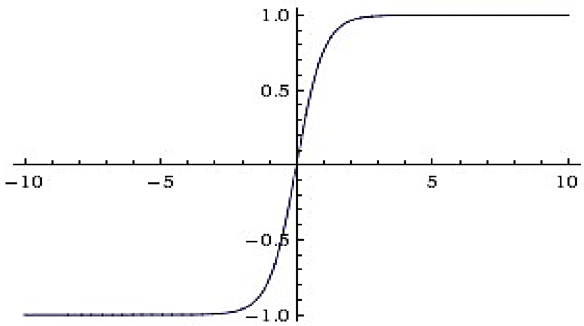


Figure 6-8: The hyperbolic tangent activation function.

Figure 6-8 represents a hyperbolic tangent activation function $Tanh(S)$ which fires the threshold rate of O for the value of summation function of S in a range between $[-1, 1]$ by the partial derivative:

$$O = Tanh(S) = 2\sigma(2S) - 1 \tag{6-14}$$

$Tanh(S)$ is also noted as the scaled Sigmoid activation function since it unlike the Sigmoid which fires a threshold rate in a range between $[0, 1]$, rates this value in a range between $[-1, 1]$ (Github, 2016).

6.6.2 The Artificial Neural Network Topologies

An ANN topology aims at determining the organisation of the neurons and the interconnection between them within a number of layers between the neurons in the input and output layers. In addition, the topology regulates a neuron in a layer by the way it is allowed to communicate with other neurons in the network. The ANN topologies apply different graph theories to structure an ANN by considering a neuron as the node of a graph and connections as edges of the graph (Priddy and Keller, 2005).

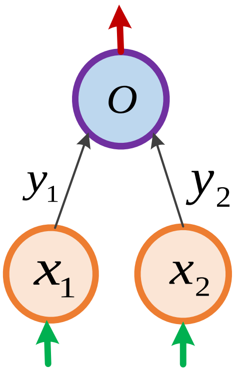


Figure 6-9: A simple ANN.

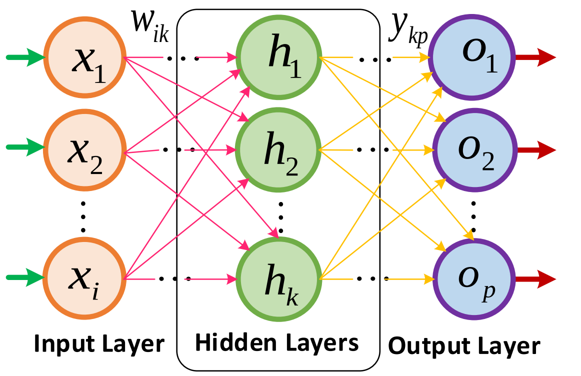


Figure 6-10: A multilayer feed-forward ANN.

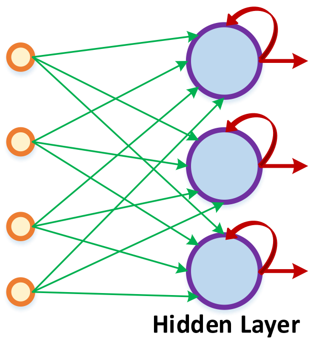


Figure 6-11: A basic recurrent ANN.

For instance, Figure 6-9 represents a simple ANN comprising only two layers. One layer receives inputs from x_1 and x_2 when a neuron in the other layer fires the output O. Figure 6-10 represents a Feed Forward Artificial Neural Network (FFANN) which directs the data flow from the input neurons by vector $\vec{I}$ (Equation 6-9) forward through a k number of neurons in each hidden layer by vector:

$$\vec{H} = [h_1, h_2, h_3 , \cdots , h_k] \tag{6-15}$$

and each connection between neurons in different middle layers is weighted by w_{ik}, and in the last layer which connects the network to the output layer, by y_{kp}.The output of the network, vector:

$$\vec{O} = [o_1, o_2, o_3 , \cdots , o_p] \tag{6-16}$$

fires threshold rates through neurons in the output layer which are weighted by y_{pk}. The vector O is measured by:

$$\vec{O} = f_{O_p}(\sum_k y_{kp} f_{h_k}(\sum_i w_{ik} x_i)) \tag{6-17}$$

The values in vector O publish the result(s) of the network which can be applied to solving a classification, prediction or calculation problem.

Unlike the FFANN which allows no cycle between different neurons in the network, a recurrent ANN, as was shown in Figure 6-11, *allows neurons to feed themselves or neurons in the previous layers by feedbacks. This creates an internal state of the network which allows it to exhibit dynamic temporal behaviour* (Graves, Liwickiet, Fernandez, Bertolami, et al., 2009, p. 856).

Sometimes, an ANN is also fed with a bias neuron besides other input neurons. The bias value enables the network to shift the activation function over the horizontal axis to modify the point where a neuron has to fire (Gosavi, 2014). Figure 6-12 depicts how the bias node influences the activation function $\sigma(w_0 * x + w_1 * 1.0)$ where a weight of -5 for w_1 shifts the curve to the right, which allows having a network that outputs 0 when x is 2 (RazorSyntax, 2016).

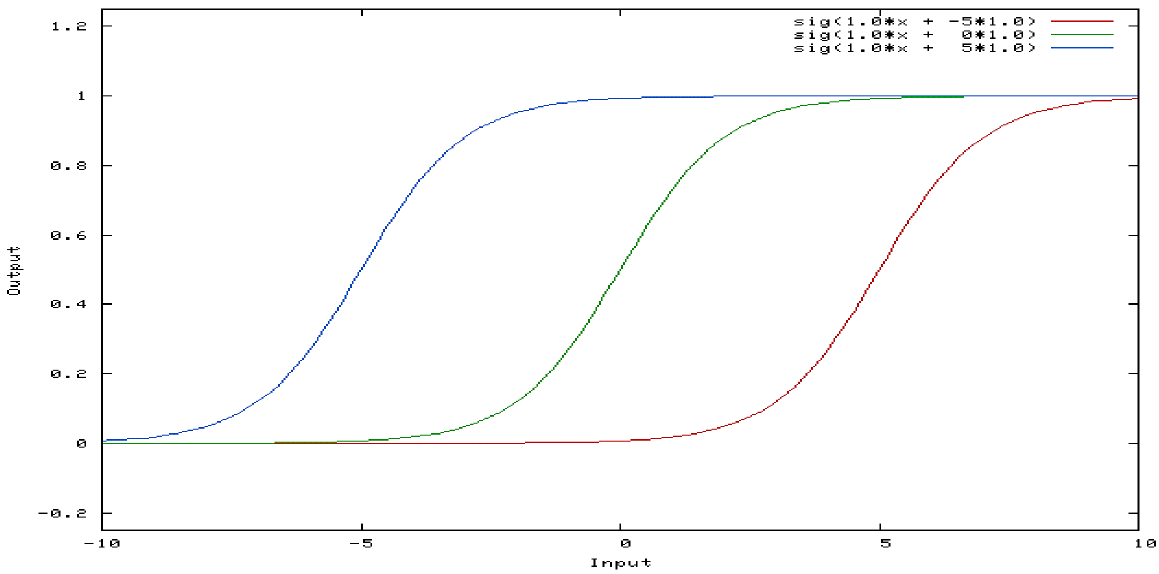


Figure 6-12: The effect of a bias node onto a Sigmoid activation function.

In an ANN which is fed by the bias neuron x_b as well, the neurons in the input and middle layers' vectors respectively would be an expansion of Equation 6-9 and Equation 6-15 to:

$$\vec{I} = [x_1, x_2, x_3, \cdots, x_i, x_b] \tag{6-18}$$

$$\vec{\mathrm{H}} = [\mathrm{h}_1, \mathrm{h}_2, \mathrm{h}_3, \cdots, \mathrm{h}_\mathrm{k}, \mathrm{h}_\mathrm{b}] \tag{6-19}$$

6.6.3 The Backward Propagation of Errors Learning Algorithm

A learning algorithm is applied to a network to construct a model for it. Basically, the model determines the weight of connections in the network with the aim of enabling the network to measure the outputs for a given set of inputs, as possibly equal as the desirable value (Priddy and Keller, 2005). As was pointed out in Section 5.9, the learning process can pursue either a supervised or unsupervised learning paradigm. The supervised learning paradigm approaches a network to learn specific patterns from a given set of labelled examples. This allows the network to make a decision based on the probability of new examples and label them (Mohri, et al., 2012). An unsupervised learning paradigm, however, is applied when there is no specific clue with regard to the expected or anticipated output. The unsupervised learning forms a self-learning ANN (Moein, 2014).

There is a variety of training algorithms to train a model for an ANN. According to MathWorks (2016), *it is very difficult to know which training algorithm will be the fastest for a given problem. It depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression)*.

A Backward Propagation of Errors (Backpropagation) is a popular Error-Correction Learning technique to train a model for an ANN. Backpropagation is commonly used for supervised training an FFANN where it compares the predicted output values to the expected values. The error rate of this comparison can be measured by the Mean Squared Error (MSE) function which explores the accuracy of a prediction by representing the differences between the expected and predicted values for a given set of inputs. The MSE value for a network with p number of neurons at the output layer which is fed by the n number of data rows in a training dataset can be calculated by (Chiulli, 1999):

$$\xi_n = \sum_p (E_{pn} - O_{pn})^2 \tag{6-20}$$

$$MSE = \frac{1}{n} \sum_n \xi_n \tag{6-21}$$

where vector O represents the values at the output layer for the n^{th} row of data in the training dataset and E represents the expected value for that output neuron.

According to Raul Rojas (2013), the backpropagation algorithm performs the training by an iteration in the two following steps:

1. ***Feed-forward:*** The output value(s) of the ANN will be calculated for each pattern when the network is fed by a training dataset.
2. ***Backpropagation:*** The training algorithm passes the error rate backwards through the network to continue training and updating the weight of connections via a multiple number of iterations with the aim of minimising the error rate.

The backpropagation algorithm measures a change in the error function value when it modifies a weight w_{kn} between a neuron n and the neuron k in the previous layer. The error function (Equation 6-21) for each neuron can be calculated by the partial derivative of (Ke-Lin and Swamy, 2014; Makin, 2006; Riedmiller and Braun, 1993):

$$\frac{\partial \xi}{\partial w_{kn}} = \frac{\partial \xi}{\partial O_n} * \frac{\partial O_n}{\partial net_n} * \frac{\partial net_n}{\partial w_{kn}} \qquad (6\text{-}22)$$

where O is the triggered value of the neuron n and the net_n can be measured by Equation 6-11 for that neuron. The value of this function (Equation 6-22) would be passed through an activation function as well. For instance, if the network employs a Sigmoid activation function (Equation 6-12), then by putting Equation 6-22 into Equation 6-13, a weight in the network would be updated by the formula:

$$\frac{\partial \xi_n}{\partial y_{kn}} = -(E_n - O_n)O_n(1 - O_n)O_k \qquad (6\text{-}23)$$

When the algorithm has calculated the partial derivative for each weight in the network for the first time, it has to minimise the error rate by updating this value for the given training dataset while it investigates whether overfitting has occurred. Overfitting refers to a point where the network has memorised the patterns in the training dataset with the least error value, but it is not able to generalise new given examples. The iterations of the training algorithm can be frozen once the network is appropriately familiar with patterns and a predetermined least error rate is approached (Shmueli, Patel and Bruce, 2011).

There are various algorithms to perform the minimisation of error values. For instance, a gradient descent function is commonly applied to the training algorithms for the ANNs in which the function uses a set of parameters to calculate the adjustment rate of a weight precisely (Mehrotra, et al., 1997). For instance, it can be performed by a momentum-term in a gradient descent algorithm which is calculated by:

$$\Delta w_{kn}(t) = -\,\varepsilon \frac{\partial \xi_n}{\partial w_{kn}}\,(t) + \mu \Delta w_{kn}(t-1) \tag{6-24}$$

where ε is the learning rate used to scale the value of partial derivative and μ is the momentum parameter to *rule the algorithm to take into account its movement from the previous iteration* (Wikibooks Contributors, 2013). The parameter (t) presents the old weight which has to be updated by a new weight $(t+1)$.

6.6.4 The Resilient Back Propagation Learning Algorithm

The resilient backpropagation algorithm (Rprop) is considered the best backpropagation algorithm, measured in terms of convergence speed, accuracy and robustness within training parameters (Bhavani Sankar, Seethalakshmi and Kumar, 2011). According to Riedmiller and Braun (1993), the developer of Rprop, the algorithm takes into account if the sign of the partial derivative is changed when it is compared to the last iteration. They have also introduced the pseudo-code presented in Figure 6-13 which can be applied to the implementation of an Rprop algorithm.

For all weights (and biases) {

  if $\left(\frac{\partial \xi}{\partial w_{kn}}(t-1) * \frac{\partial \xi}{\partial w_{kn}}\,(t) \geq 0\right)$ **then {**

    if $\left(\frac{\partial \xi}{\partial w_{kn}}(t-1) * \frac{\partial \xi}{\partial w_{kn}}\,(t) > 0\right)$ **then {**

      $\Delta_{kn}(t) =$ **minimum** $(\Delta_{kn}(t-1) * \eta^{+}, \Delta_{max})$

    }

    $\Delta w_{kn}(t) = -$ **sign** $(\frac{\partial \xi_n}{\partial w_{kn}}\,(t)) * \Delta_{kn}(t))$

    $w_{kn}(t+1) = w_{kn}(t) + \Delta w_{kn}(t)$

    } else if $\left(\frac{\partial \xi}{\partial w_{kn}}\,(t-1) * \frac{\partial \xi_n}{\partial w_{kn}}\,(t) < 0\right)$ **then {**

      $\Delta_{kn}(t) =$ **maximum** $(\Delta_{kn}(t-1) * \eta^{-}, \Delta_{min})$

      $w_{kn}(t+1) = w_{kn}(t) - \Delta w_{kn}(t-1)$

      $\frac{\partial \xi_n}{\partial w_{kn}}\,(t) = 0$

  }

}

Figure 6-13: Resilient backpropagation algorithm to train an FFANN.

In the algorithm, Δ_{kn} presents individual update-value for the weight w_{kn}, Δw_{kn} presents the size of weight-update value and η is the factor which the algorithm multiplies by weights when the sign of partial derivative $\frac{\partial \xi}{\partial \mathrm{w_{kn}}}$ was changed during the iterations. The parameter η can have a value in the range $0 < \eta^- < 1 < \eta^+$. The "minimum (maximum)" operator is proposed to deliver the minimum (maximum) of two numbers; the "sign" operator returns $+1$, if the argument is positve, -1, if the argument is negative and 0 otherwise.

To select an appropriate decrease factor η^- and increase factor η^+ needs considering that if a jump over a minimum occurred, the previous update-value was too large. The gradient information exposes how much the minimum is missed. The increase factor η^+ has to be large enough to allow fast growth of the update-value in shallow regions of the error function, on the other side the learning process can be considerably disturbed, if a too large increase factor leads to persistent changes of the direction of the weight-step (Riedmiller and Braun, 1993, p. 590).

6.7 Architecture of the Prototype

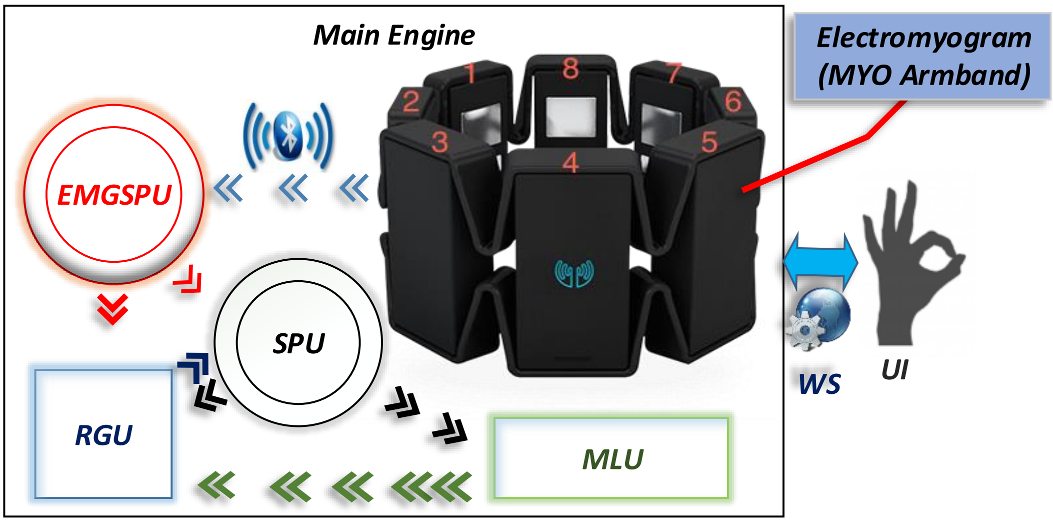


Figure 6-14: Proposed architecture for the MCIp using a MYO Armband.

Figure 6-14 represents the proposed architecture of the MCIp which is designed and implemented by using the JAVA programming language and which satisfies the needs and expectations for the proposed MCI by making use of the MYO Armband. The architecture consists of a main engine which includes an EMG Service Provider Unit (EMGSPU – Section 6.7.1), a Signal Processing Unit (SPU – Section 6.7.2) and a Machine Learning Unit (MLU – Section 6.7.3). A Report Generating Unit (RGU –

Section 6.7.4) and a User-Interface (UI – Section 6.7.5) which communicates with the system through a web service (WS) are also included.

6.7.1 EMG Service Provider Unit

The EMGSPU acquires signals for the MCIp from a MYO Armband (Figure 6-14) with a SRate of 40 *Hz,* by using an infinite running thread. Figure 6-15 plots the amplitude value (*Amp*.) of raw EMG data captured from the MYO Armband in 40.3 seconds time when the user presses each individual finger on a surface separately.

Reduction of the SRate reduced the amount of received data while giving a 25 milliseconds (*ms*) time to the system for further data-preparation processes. The EMGSPU publishes the vector $\overrightarrow{EMG}$ including eight, 8-bit integer values in a range between $[-127, 127]$ from the signals generated by each electrode ($E_1 \colon E_8$) (Figure 6-15) and can be shown by:

$$\overrightarrow{EMG} = [E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8] \tag{6-25}$$

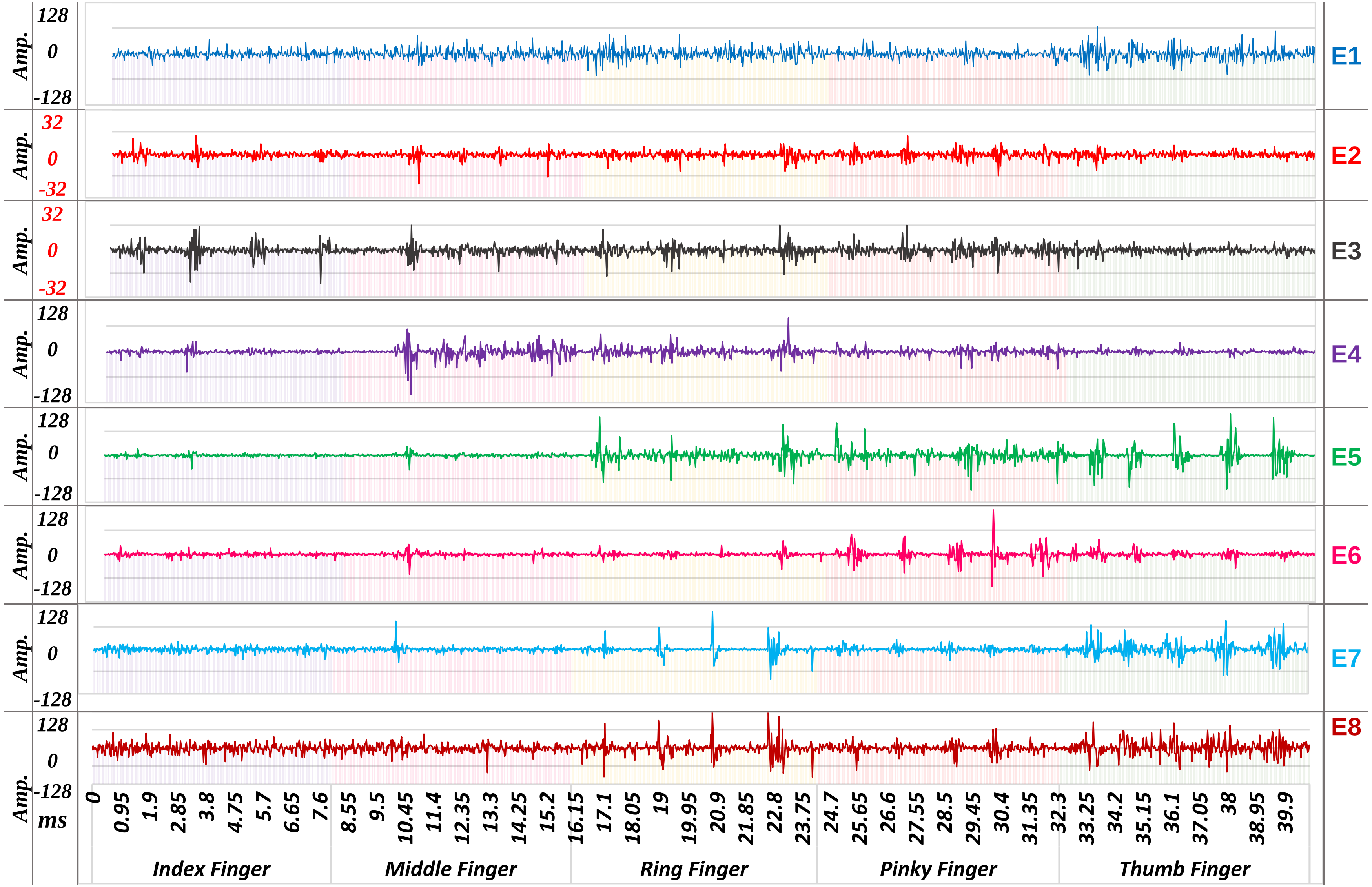


Figure 6-15: The raw EMG signals captured by the 8 electrodes (E1:E8) of a MYO Armband during 40.3 seconds (SRate of 40 Hz).

6.7.2 Signal Processing Unit

In literature there is a considerable number of reported applications of various signal processing techniques for the processing of bio-signals acquired by EMG electrodes (Arief, et al., 2015; Christodoulou and Pattichis, 1999; Katsis, Exarchos, Papaloukas, Goletsis, et al., 2007; Middleton, Christodoulou, Pattichis and Pouyiouros, 1995; Phinyomark, et al., 2012). The MCIp has implemented only the techniques identified in Section 6.5 and will be presented in Table 6-2.

The SPU instantiates a variable from the vector $\overrightarrow{EMG}$ (Equation 6-25) and passes it through an infinite running thread into a class which performs the main functionalities of this unit in a Sliding Window with a size of 25. The class pushes $\overrightarrow{EMG}$ into a sequence of different functions each of which performs only one specific process with the data. Then, at the end, as the output, the class publishes the vector $\vec{I}$ (Equation 6-9) including an array of values of features from the Polynomial Curve Fitting and the Wavelength (each generates an array with a size of eight values for eight electrodes) and the matrix of Convolutions with a size of twenty-eight values (measured by the Equation 6-6, when $n = 8$).

Table 6-2 plots the data in vector $\overrightarrow{EMG}$ when the vector passes through the different functions in the class, the priority of applying each function (*Seq.* – the Wavelength and Convolution are calculated parallel as they both require the value of curved RMS signals). The plotted signals from each electrode (E1:E8) are presented upon an axis of amplitude (*Amp*. – velocity of signals in a specific range) and an axis of time in seconds. The data is recorded within a 3 seconds time frame.

The vector $\vec{I}$ is published to be used by the MLU later. The vector exposes the different features from each gesture in a more understandable manner. Therefore, the value x_i as the i^{th} member of output vector $\vec{I}$, should be a value in the range between $[0, 1]$, as the classifier requires to be fed with values in this range (Section 6.6.1).

Table 6-2: Plotting signals when they are processed by the SPU.

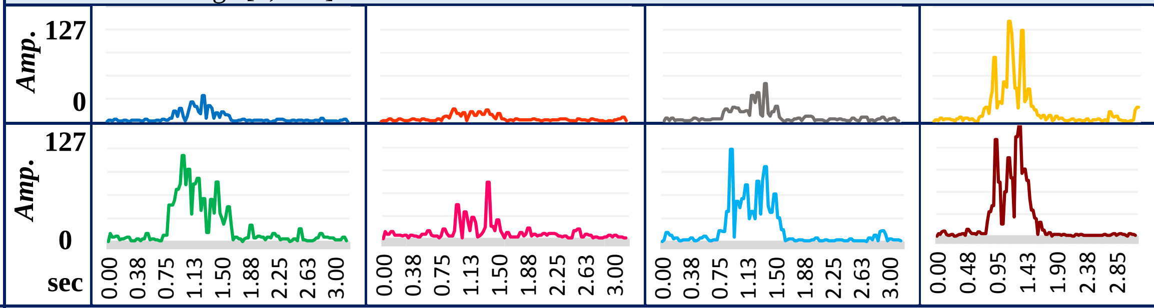
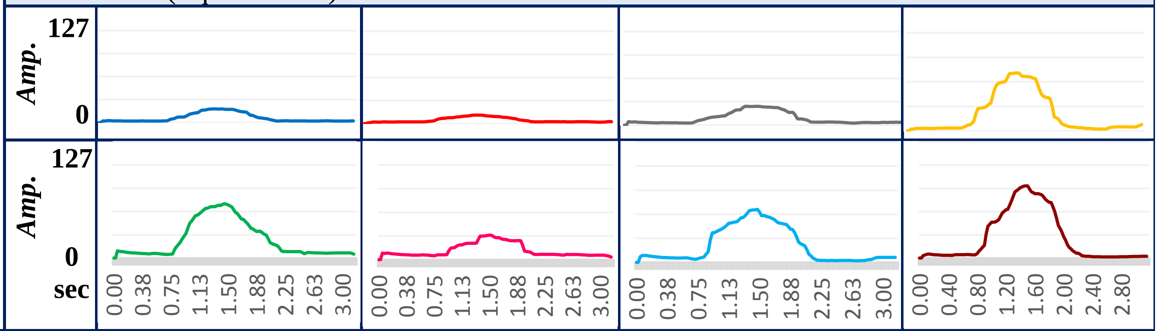
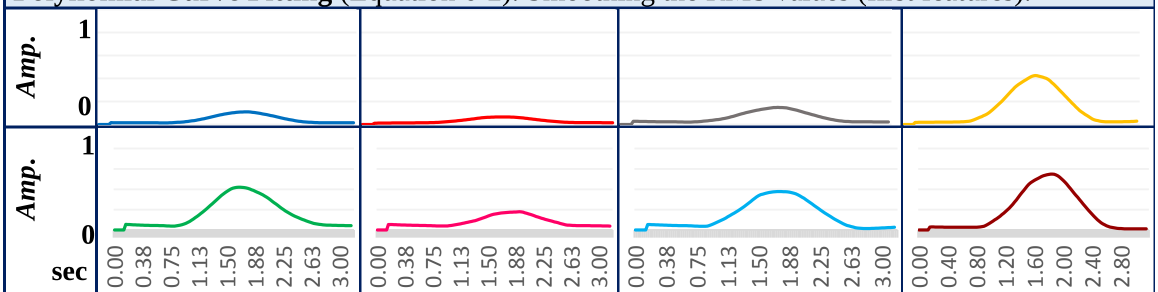
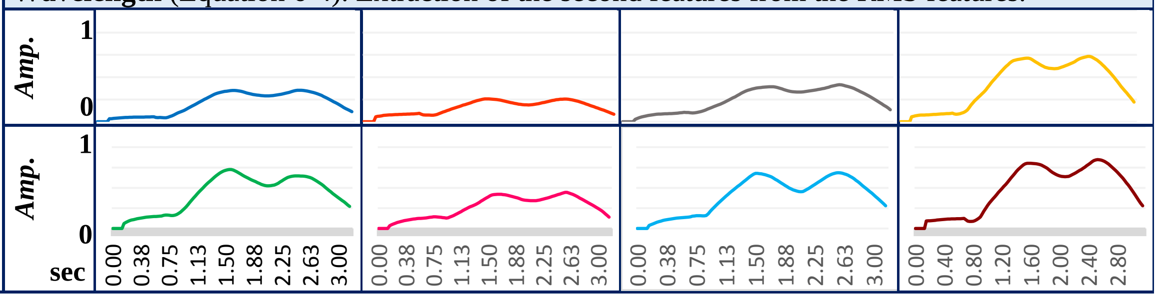
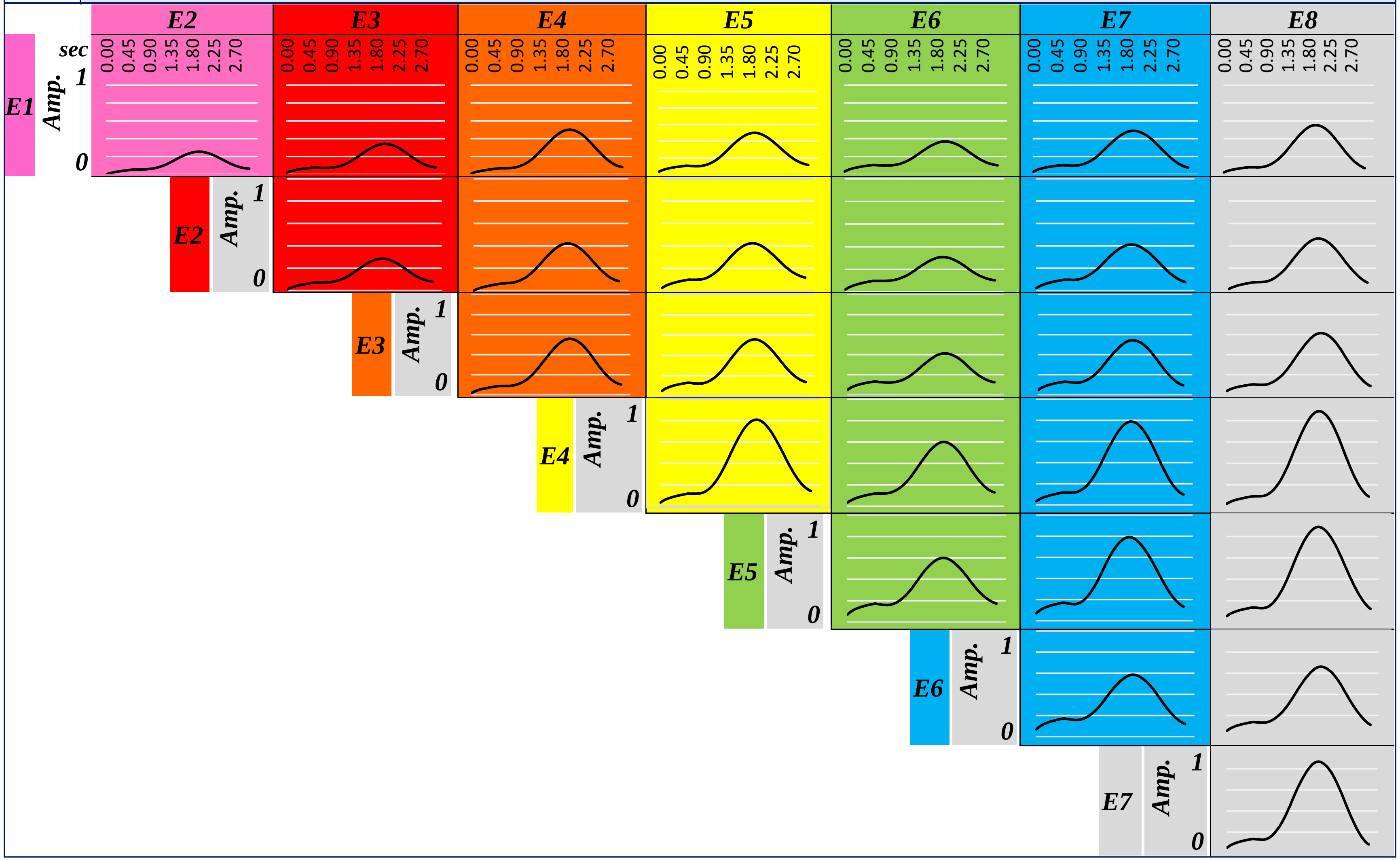
Seq.	***Signals Plot***
	Electrodes: E1 E2 E3 E4 E5 E6 E7 E8
1)	**Min-Max Normalisation** (Equation 6-1). Reducing the inconsistency in data and bringing all values into the range [0, 127].
	
2)	**RMS Value** (Equation 6-3).
	
3)	**Polynomial Curve Fitting** (Equation 6-2). Smoothing the RMS values (first features).
	
4)	**Wavelength** (Equation 6-4). Extraction of the second features from the RMS features.
	

Table 6-2: Plotting signals when they are processed by the SPU (Continue).

4)	**Matrix of Convolutions** (Equation 6-5, where the values in the matrix are calculated by the Equation 6-8). Extraction of the third features.



6.7.3 Machine Learning Unit

There are reported applications in literature of the unsupervised learning paradigm in the recognition of motor unit spikes acquired by EMG electrodes (Christodoulou and Pattichis, 1999; Katsis, et al., 2007; Middleton, et al., 1995). The MCIp, however pursues a supervised learning paradigm in order to classify the EMG signals. There are also various topologies reported to model ANNs (Abbaspour, et al., 2016; Hua, et al., 2015; Valbuena, et al., 2010). The MCIp constitutes an FFANN (Section 6.6.2) which receives the vector $\vec{I}$, with 44 values in it, from the SPU at the input layer and labels the six gestures of each gesture-group (Table 6-1) by vector $\vec{O}$ through 6 output neurons.

The MCIp applied the Rprop algorithm (described in Section 6.6.4) to train a model for the ANN. In order to perform an optimised and accurate training process, the algorithm requires a configuration and a setting of some necessary parameters. As there is no specific rule in literature to set these parameters appropriately and as it has been repeatedly reported as a rule of thumb, first, a recursive function modified the parameters iteratively to present the influence of the modification of the parameters upon the predictions of the network. This process will be explained and depicted in Section 6.9.1. The parameters and the way the function determines them are listed below (Priddy and Keller, 2005):

1. ***Size of training dataset***

   Because of the current strategy applied to the training, the algorithm uses a pre-captured training dataset which is labelled and presented to it. The size of the training dataset impacts the time taken by the algorithm to optimise the error rate (Equation 6-21). Naturally, a larger training dataset presents more data to a network and relatively increases the accuracy of network's predictions in the future.

2. ***Number of iterations (epoch) to train a model***

   The function checks if the number of epochs crosses the threshold rate and then it recursively initiates itself after the modification of the number of hidden layers and neurons in each layer. It is supposed that a well-structured network will be modelled in a smaller number of iterations.

3. ***Desirable error rate***

   When the training algorithm iterates to minimise the value of the error function, a desirable value should be set to freeze the iteration and update the value of weights. In the MCIp, the function stops the iteration once a desirable error rate is approached.

4. ***Update-value (Δ)***

   This parameter directly determines the size of the first weight-step, it is preferably chosen in a reasonable proportion to the size of the initial weights (Riedmiller and Braun, 1993). A range between the initial update-value of $\Delta = \mathbf{0.1}$ and maximum update-value of $\Delta = \mathbf{50.0}$ was set while training the model.

5. ***Number of hidden layers***

   As will be presented in Section 6.9.1, after evaluating a network with no hidden layers, a primary hidden layer containing a bias node was added. Both results were evaluated and the result of this evaluation is plotted in Section 6.9.1 and the selected value for this parameter in also presented in Figure 6-16.

6. ***Number of neurons in the hidden layer***

   The number of neurons in a hidden layer has a considerable influence on the time each iteration takes as it directly determines the dimensionality of the weight vector (Naoum, Abid and Al-Sultani, 2013). In order to find an appropriate number of neurons in the hidden layer, the function evaluated the predictions' accuracy while modifying the number of neurons with each value in the range between $[1, 250]$ (Section 6.9.1).

7. ***Activation function***

   The Sigmoid Activation function (Equation 6-12) is used in all neurons in the input, hidden and output layers.

Figure 6-16 presents the preferred network which was modelled to be used in the MCIp. Once the model was created, a configuration file containing the values of weights and number of neurons in different layers was stored to be used later to model the network for different users quickly. This entire process is referred to as the calibration of the MCIp, enabling it to label a stream of EMG signals by each gesture. In order to apply the MCIp in the real world as an HCI device, the MLU receives a stream of data from the SPU continuously and asks the modelled ANN to label it.

The highest value fired by an output neuron indicates the label of each gesture the incoming signal belongs to.

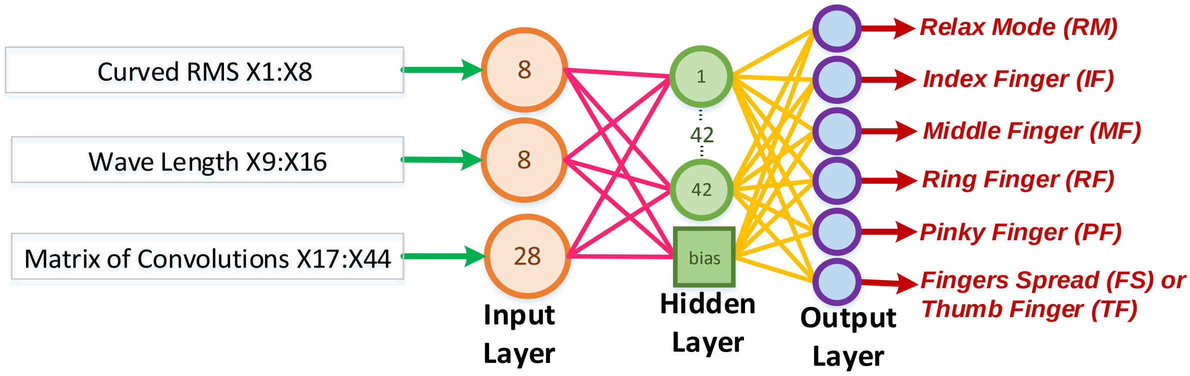


Figure 6-16: The structure of the proposed network for the MCIp.

The MLU receives $10^3/EMG_{Srate}$ lines of raw EMG data in one second which may either contain an inaccurate or accurate prediction by determining a neuron with the highest value as the classification result. To smooth incoming results and ignore uncertain recognitions, an array rates a recognised label and the un-rating of other labels by giving each label a value between the range $[0, Sliding\ Window\ Size]$. Then, the MLU streams this array to the UI by publishing a global variable.

The Encog Machine Learning framework was used that allowed for the training and creation of the FFANN by using its multi-thread processing ability and Rprop capabilities (Heaton, 2015).

6.7.4 User-Interface

The MCIp allows users to interact with the system through its built-in web-based UI which communicates with the main engine by using AJAX technology. The main engine provides access to different functionalities or values of variables with a JavaScript Object Notation Web-Service Protocol (JSON-WSP) web-service as its gateway.

The current version of the MCIp aims to evaluate the feasibility of this type of interaction rather than focusing on designing a working-version solution to the real-world users. Therefore, during the design there was no emphasis on considering usability issues of the MCIp and on the design of the UI for a specific goal. The list below gives a brief explanation of functionalities which the UI gives to MCIp users in the current version:

1. Select either calibration or evaluation consoles, start or stop the armband, calibrate the MCIp (training an ANN) and change the Sliding Window size using the menu (Figure 6-17).
2. Create or append a training dataset for one gesture in a gesture-group by giving it a unique numeric value, for a specific duration of time in seconds (Figure 6-17).
3. Give feedback to the user in order to express the current state of gesture recognition (Figure 6-18).
4. Allow the user to enter the given barcode number provided on the screen, using finger gestures (Figure 6-18).

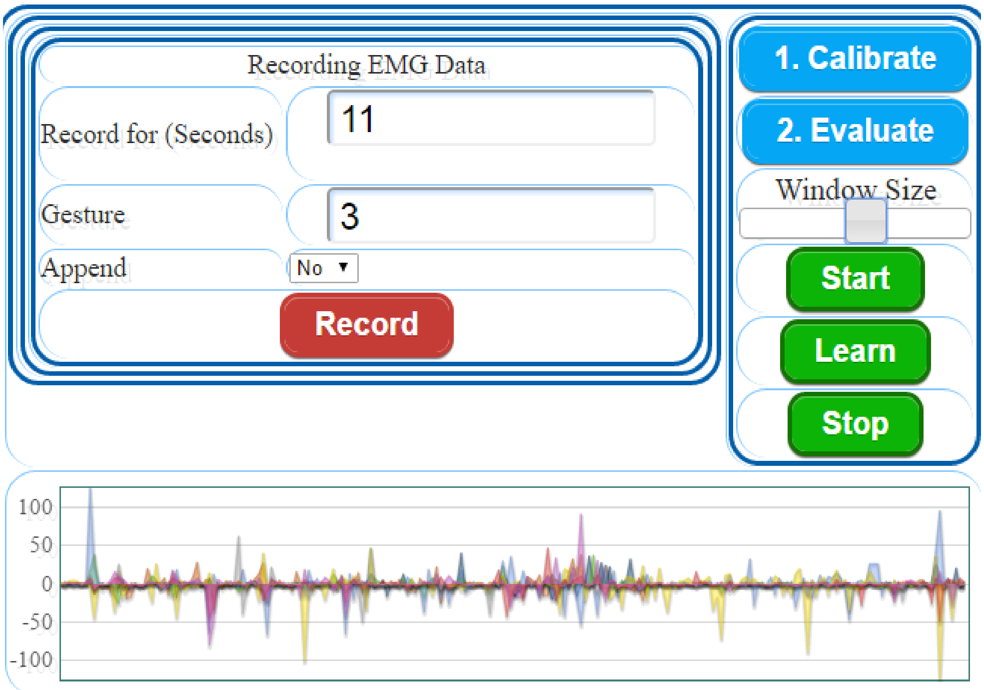


Figure 6-17: Main screen and calibration console screenshot.

Figure 6-18: Evaluation console screenshot.

The UI receives the array of predictions from the MLU and presents it to the user via a percentage in the bars (Figure 6-18). To make sure that the user intends a certain gesture, when a bar fills from 0% to 100%, the UI selects this as the desired input and immediately prevents further input before the user fills the relax mode bar to 100% value. Figure 6-17 and Figure 6-18 represent the proposed UI and explain each component. A detailed explanation of all the components of UI (Figure 6-17 and Figure 6-18) is attached to Appendix F as well.

6.7.5 Report Generating Unit

The main aim of the RGU is to collect, manage and archive the raw EMG data from a user's activities in the text format with the aim of conducting further analysis on the data. In general, the activities include calibration and task completion. This unit is implemented by a function which creates a file for each gesture and saves it in an organised manner to be used later for the training and evaluating the MCIp.

After the completion of the calibration stage, this unit evaluates the generated network by feeding it with the entire training dataset again. Then, it generates a spreadsheet and reports the results of the evaluation. The report includes the training dataset, ideal values and the predicted values.

6.8 Experimentation

In order to evaluate the potential of the MCIp as a desirable solution to solve the existing problem in input provision to a WMS (Section 1.2), an experiment was designed to investigate the efficiency and effectiveness of the current prototype when it was faced with a real-world problem. Therefore, only the gesture classification and providing numeric inputs provision capabilities were implemented and evaluated.

To achieve both aims, some participants were recruited to perform some tasks using the MCIp when an investigator assisted them with the procedures involved in the experimentation and tasks completion. The experiment was conducted within two different experiment sessions. The first session was mainly focused on evaluating the performance and accuracy of the MCIp and the other session on the evaluation of the MCIp's efficiency when it was applied as an input provider device to a semi-similar real-world situation.

Before each experimentation, the investigator requested the participants to complete a consent form attached to Appendix C, in order to make sure the participants were willing to participate in the experimentation. Then, the participants were requested to read and sign the written (Appendix D) and oral information (Appendix E) prior to the participation, in order to inform them about all aspects of the experimentation. And finally, they were asked to complete the biographical and user experience questionnaire (Appendix B).

6.8.1 Participants Recruitment

To evaluate the effectiveness and efficiency of the MCIp, a group of eight participants with no muscular or skin condition were used from the NMMU Computing Sciences postgraduate students. Two participants had prior experience with using an MCI and the others were novices. Table 6-3 presents the biographical details of the participants.

Table 6-3: The specification of participants.

Participant	*Race*	*Gender*	*Dominant Hand*	*Age Range*	*Experienced*
P1	Asian	**Male**	Right	**30-35**	**Yes**
P2	African	**Female**	Right	**18-25**	**No**
P3	African	**Female**	Right	**18-25**	**No**
P4	African	**Male**	Left	**18-25**	**Yes**
P5	African	**Female**	Right	**18-25**	**No**
P6	African	**Male**	Right	**18-25**	**No**
P7	African	**Male**	Right	**18-25**	**No**
P8	African	**Female**	Right	**30-35**	**No**

6.8.2 Setup

After the participants completed the necessary forms and accepted the conditions of participating in the experiment, the investigator, considering the circumference of the forearm of each participant, adjusted the Myo Armband's size. Then, the investigator slid the armband over the participant's forearm muscles of the dominant hand and placed it directly below the elbow (as was depicted in Table 6-1 and Figure 5-37). For the entire duration of the experiment, the armband had to fit comfortably. It was furthermore checked that it was not too loose so that it would not slip around the forearm when the participant moved his/her hands nor if it were struck by an object. The participants were requested to prevent slight movements of the armband.

6.8.3 Experimentation-1

Experimentation-1, the participant was asked to sit on a chair with his/her back comfortably supported and with the elbow of the dominant hand lying on the chair's armrest. The participant was also asked to keep the forearm and hand bent at roughly a ninety-degree angle (Figure 6-20) for the entire training and task completion time. Then, in order to create a training dataset, the investigator captured EMG signals for each gesture over a period of 10 seconds. The participant was continuously maintaining the gesture for about 1 second and then relaxing the muscles for 1 second (approximately 3 positions were captured for each individual gesture).

The MCIp generated a predetermined and fixed sequence of 35 numbers (the digits ranged between 1 and 5 since only one hand was used) in which each digit was presented on a large-size screen to each participant separately via the UI. Then, the participant was required to use the MCIp input method to insert each represented number by performing a pinch gesture (as was depicted in Section 6.5.1, Table 6-1, gesture-group I) using a finger which was encoded as one digit (as the encryption of fingers into digits was depicted in Figure 6-18, at the right side of each bar).

6.8.4 Experimentation-2

As was explained in Section 4.9.1, in a warehouse environment, workers generally carry items which include boxes. In order to reduce the impact of the non-stationary state of bio-signals (Section 6.4), instead of designing and offering a complicated computational solution to measure and influence variables on EMG signals, the MCIp used customised gestures within the gesture-group II (as was depicted in Section 6.5.1, Table 6-1) and introduced a change in the method of handling materials as is depicted in Figure 6-20. In this method, the participant was required to hold and lever the box by putting one hand under the load and using the surface of box as an armrest for the input-generating hand. In this way, the participant was able to hold the box in a stable position.

Figure 6-19: A participant's position in the Experimentation-1.

	Box 1	*Box 2*	*Box 3*
Dim:	*38*32*25 (Cm)*	*40*13*40 (Cm)*	*40*40*13 (Cm)*
Weight:	*2.7 Kg*	*1.2 Kg*	*1.2 Kg*

Figure 6-20: Manual material handling method and hands placement of a participant in Experimentation-2 (dimensions: Width * Length * Height in centimetres, and weight in Kilograms).

During the training time, the investigator requested the participant to sit on a chair with his/her back in a supported position with his/her forearm lying down at a tangent to the surface of a table with the edge of the table positioned closely to the armband (Table 6-1, gesture-group II – the MYO Armband's placement and relax mode). This is to reduce the tension in the forearm muscles. The participant was requested to posture gestures in this position. The investigator captured EMG signals for each gesture over a period of 10 seconds, as the participant continuously postured the gesture for approximately 1 second intermittently, relaxing their muscles for the other second (approximately 3 positions were captured for each individual gesture).

Three different box sizes were selected (Figure 6-20) in order to prevent the participant from experiencing tension or frustration due to weight and size. The investigator requested that the participants stand up straight and hold each box in both hands while completing the tasks. The MCIp generated an EAN-13 barcode number (digits ranged between 1 and 5 since only one hand was used) presented on a large-size screen and the participant was required to use the MCIp input method to insert five different barcode numbers within tasks.

6.9 Evaluation Experiment and Analysis Results

To measure the efficiency and effectiveness of the MCIp and compare it with an acceptable solution, a general evaluation with three main objectives was performed on the data collected from the experimentations. The first objective was to observe the behaviour of the training-function process when it was applied to create an appropriate model for the ANN (Section 6.6.3) Secondly, to evaluate the influence of the implementation of Signal Processing and Feature Extraction techniques on the performance of the ANN and thirdly, the evaluation was performed to measure the accuracy of the ANN's predictions as well as the performance of gesture recognition when the system was applied to a real-life situation.

6.9.1 Evaluating the Training-Function for the Artificial Neural Network

As was identified in Section 6.7.3, the MLU applied the training-function to determine the necessary parameters to configure the FFANN and train a model for it by using the Rprop training algorithm. In the beginning, experimentation was conducted to observe the performance of a network which was formed only by connections between neurons at the input and output layers. The network was provided with a training dataset with the size of 1500 data rows with each row containing 44 dimensions (the training dataset was recorded during the Experimentation-1 – Section 6.8.3 – from one of the participants).

As it can be observed in Figure 6-21, the error rate (Equation 6-21) falls off after 50 epochs into a value less than 0.05%, but even after 5000 number of epochs the function could not satisfy the least allowed error rate of 0.005%.

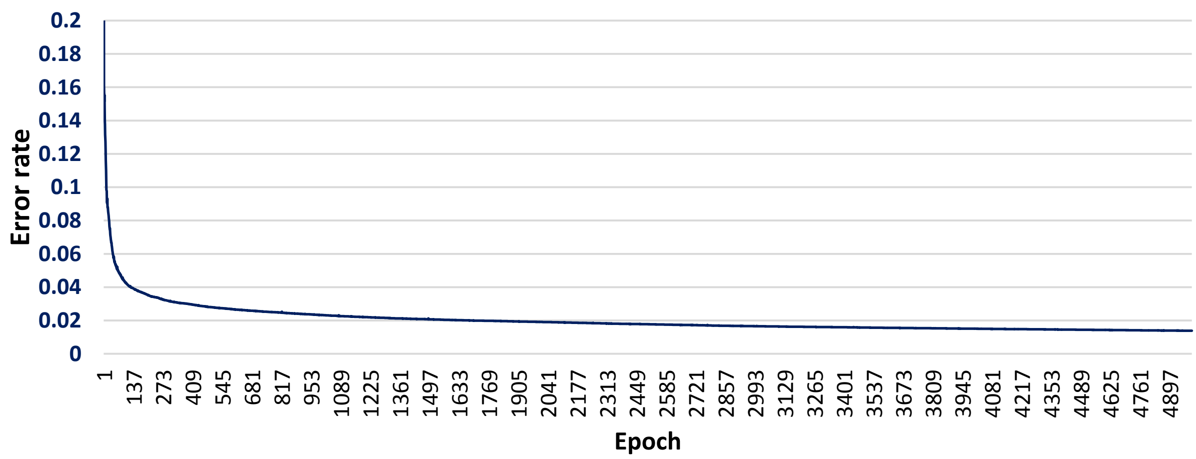


Figure 6-21: Evaluation of the error rate while training an FFANN with no middle layers, within 5000 epochs.

A middle layer was then added manually to the network and the function was run again to investigate the error rate when the number of neurons in the middle layer was modified incrementally. Figure 6-22 plots the error rate returned by the training algorithm when it was run with the training-function during a period of 2000 epochs for a number of neurons in a range between $[1, 250]$ in each iteration.

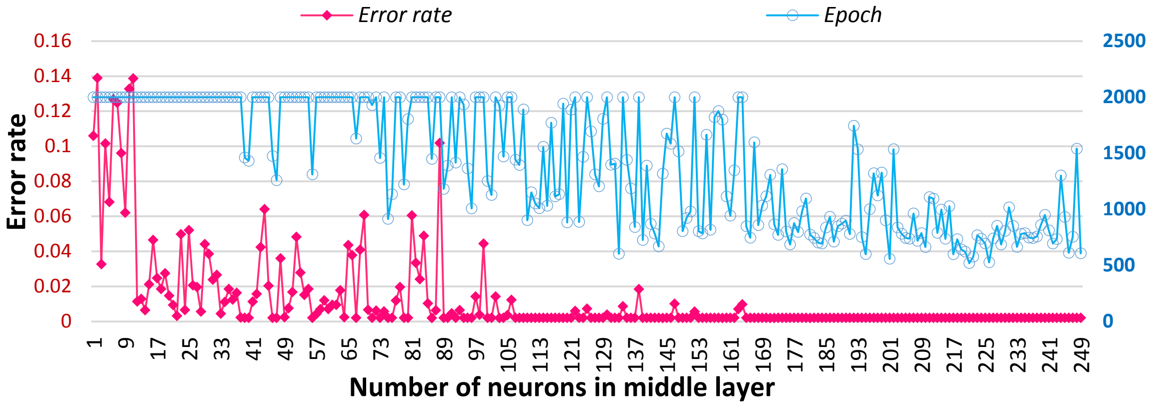


Figure 6-22: Evaluation of the network's performance when the number of neurons in the middle layer was in a range between [1, 250].

As can be observed in Figure 6-22, the trend of approaching an acceptable error rate remained at the same rate when there were more than 90 neurons in the middle layer as the number of epochs reduced as well. As was explained in Section 6.7.3, when the number of neurons increases, the amount of time taken by the training increases as well, as can be observed in Figure 6-23. In addition, a network with a greater number of neurons in the middle layer memorises an entire pattern instead of learning its behaviour. This can cause an overfitting as well.

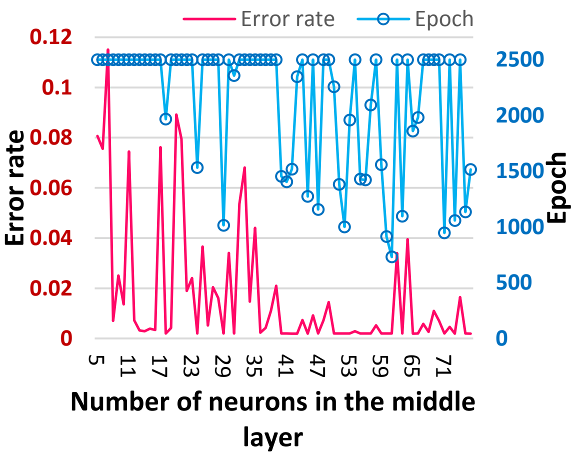


Figure 6-23: The value of the error rate during the training time with number of epochs.

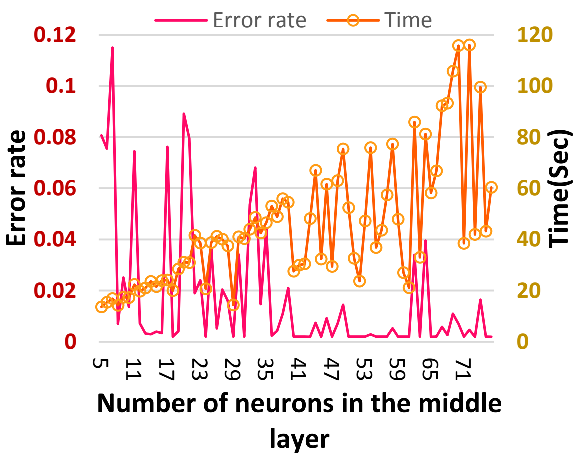


Figure 6-24: The value of the error rate during the training time with number of neurons in the middle layer.

As the training process had an acceptable error rate when the network had less than 90 neurons in the middle layer, another experiment was only conducted for a number of neurons between the range $[5, 77]$ and ignored other values of this parameter. This time the experimentation was conducted within a number of 2500 epochs. The results of this experiment are plotted in Figure 6-23. In addition to the criteria that were considered in the previous experimentation, as can be seen in Figure 6-24, the amount of time taken by the training process was also considered in this experimentation.

As can be interpreted from a comparison between the results in Figure 6-22 and Figure 6-23, the training algorithm has a different behaviour each time it is run even with the equal number of neurons in the middle layer. This is because of a random value which the training algorithm selects for the update-value Δ in the range between $[0.1, 50]$ in each iteration. Therefore, in the second experimentation the results were measured by the average value of error rate, the number of epochs and time when the training-function was run five times for the only one training dataset.

However, as is presented in the figure, the model was constructed with fewer than 40 and more than 18 neurons in the middle layer and the ANN with the greater number of neurons in the middle layer was modelled within an acceptable time as well. Because of the complexity of bio-signal classification (Section 6.4), the model could not be constructed for different users when it had fewer than 40 neurons in the middle layer within the limited number of epochs when the model was trained with different training datasets. Therefore, the value of this parameter was manually modified many times to find an appropriate value for this parameter. Consequently, a model with a number of 42 neurons in the middle layer was constructed for this specific problem. The training time for constructing this model was 29 seconds on average.

6.9.2 Evaluating the Effects of Signal Processing and Feature Extraction Techniques upon the Performance of Data Classification

To measure the performance of the data classification of the MCIp, the accuracy of the constructed model was evaluated when it was provided with each feature (Section 6.5.3) extracted from one of the training datasets collected during the experimentation-2 (Section 6.9.1). This experimentation was conducted only to measure the accuracy of the network when it was fed with the same dataset, but with different features.

The accuracy of the predictions was then evaluated by measuring the Root-Mean-Square Error (RMSE). RMSE explores the accuracy of a prediction by representing the differences between the expected and predicated values for a given set of inputs.

The RMSE value for a dataset with the size of n containing predicted values of p and expected values of e is computed by the formula (Vastrad and Doreswamy, 2013):

$$RMSE = \sqrt{\frac{\sum_{k=1}^{k=n} |p_k - e_k|^2}{n}} \quad (6\text{-}26)$$

Table 6-4 reports on error rates when using the three individual features, the curved RMS, WL and matrix of convolutions, as well as a combination of the three features. The table compares the features by considering the number of epochs while training by allowing 0.001% error rate, the training time (seconds), the number of inputs (N-o-I), and the RMSE values measured for the ANN model for each gesture (index, middle, ring, pinky and thumb – Table 6-1, Gesture-group II).

Table 6-4: The RMSE value for ANN with different features.

	N-o-I	*Epoch*	*Time*	*IF*	*MF*	*RF*	*PF*	*TF*	*AVG*
RMS	8	4864	24.47	7.59	3.27	2.91	0.07	6.44	4.05
WL	8	4772	27.72	14.92	0.22	3.0	3.10	0.005	4.24
Conv.	28	4447	119.9	3.08	8.44	1.54	0.03	6.32	3.88
RMS+WL+Conv	44	330	27.07	3.90	5.49	4.77	0.09	0.40	2.93

As can be seen in the table above, the RMS (4.05), WL (4.24), and matrix of Conv (3.88) values are approximately in the same range of error value. However, when each is compared with the combination of the three features, this combination has a lower average error rate (2.93) for all five gestures. In addition, the model would be trained within a lower number of epochs when it is fed with this combination (330 epochs), and in an acceptable amount of time (27.07 Seconds). Therefore, it can be deduced from this result that a combination of the three features provides the best results in classifying gestures in the gesture-group II. This is evident in its lowest average error rate and its acceptable amount of time and number of iterations.

6.9.3 Evaluating the Accuracy of Gesture Recognition

When a big dataset of predictions and expected values was prepared after the completion of the tasks in both experimentation sessions, as will be explained in the following sub-sections, the efficiency and effectiveness of the MCIp was evaluated in two steps. Firstly, the accuracy of the data classifier's prediction was evaluated by measuring the RMSE and the Mean Value of Predictions (MVP) to measure the accuracy of network's predictions. This was done by evaluating the results of data classification right at the output layer. Secondly, the efficiency and accuracy of the gesture recognition process at the UI was evaluated, when the system was provided with inputs.

6.9.3.1 Evaluating the Gesture Classification

Table 6-5 presents the average value for both the MVP and RMSE values, of the training and test datasets which were collected during Experimentation-1 with eight participants (a table containing the detail of results from each participant is attached in Appendix G). The results of this evaluation are also plotted in Figure 6-26 as the line charts represent the MVP values and the bars represent the RMSE values. In this experimentation, the participants were requested to posture a number of 35 gestures, 7 postures for each finger gesture.

As was mentioned in Section 6.7.4 (while explaining the UI), to provide an input a user has to complete a bar related to a gesture on the screen, and then, the system prevents any other inputs being provided before he/she fills the relax mode. Therefore, for a number of 35 gestures postured by each participant, the test dataset also included data of 34 of the RM gestures between each input. The RGU (Section 6.7.5) collects the result of the ANN's prediction from the MLU to where a requested number (encoded gesture) is sent by the UI.

Table 6-5: The RMSE and MVP values of the predictions for the training and test dataset.

			RM	*IF*	*MF*	*RF*	*PF*	*FS*	*AVG*
Average	Training	RMSE	0.0647	0.1427	0.1389	0.1859	0.1222	0.0671	0.1314
		AC	97.75%	90.32%	96.29%	97.71%	94.94%	97.93%	95.82%
	Test	RMSE	0.6959	0.5489	0.4252	0.3918	0.4023	0.4493	0.4856
		AC	30.80%	29.04%	31.31%	42.31%	38.92%	36.83%	34.87%

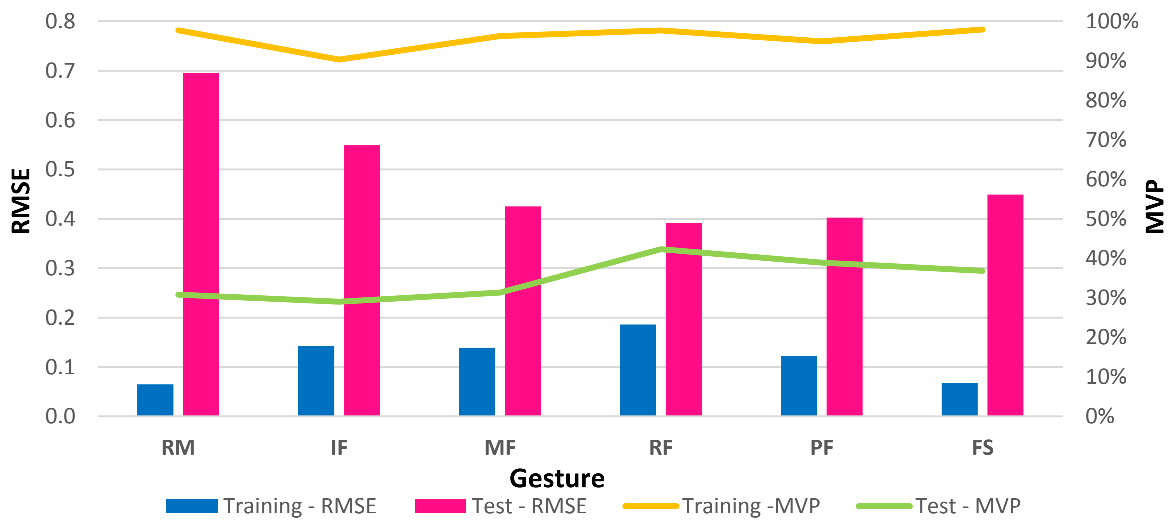


Figure 6-25: The average values for RMSE and MVP across all of the participants.

As it can be observed in the figure, the RMSE value indicates an acceptably low value when it is compared with the result of the test dataset. This is unlike the MVP value which has a high value on the train dataset. When both datasets are presented, the result is a cause of satisfaction. This result must be expected when the network classifies a trend in a non-stationary dataset.

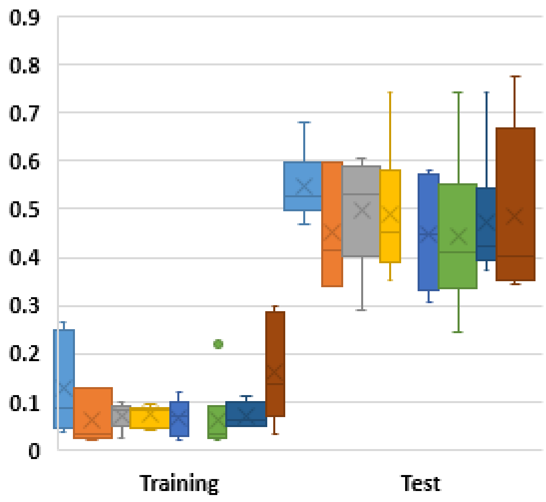


Figure 6-26: The value of RMSE for the predictions across all participants.

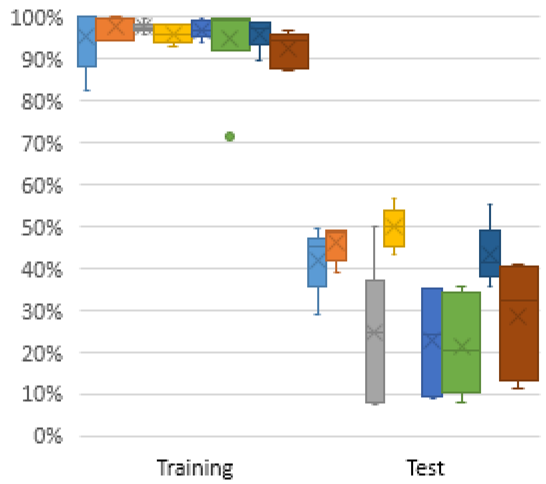


Figure 6-27: The value of MVP for the predictions across all participants.

Figure 6-26 and Figure 6-27 present a random and a specific pattern of the trends of the RMSE and MVP values across all eight participants. As it can be seen, the accuracy of predictions for either the training or the test datasets indicate that the current strategy and topology performed on this specific gesture classification task cannot be accepted as a desirable result for a prediction

6.9.3.2 Evaluating the Efficiency of Input Provision

As was explained in Sections 6.6.3 and 6.6.4, the MCIp, in order to enable the user to provide inputs, smooths the results of the gesture classification in the MLU before passing this result to the UI. Then, the user is required to complete a bar to provide an appropriate input to use the UI. To keep the user motivated and hide the possible errors of the gesture classifier from the user while collecting data for the evaluation of the MCIp's general efficiency, the user was always provided with feedback that the entry was correct even when it was incorrectly recognised. The raw result of the gesture recognition was, however, logged and used for evaluation (in a hidden field which was presented in Figure 6-18). Efficiency was measured by recording the time taken per task. In addition, accuracy was measured by recording the errors made and by comparing the provided barcodes with the barcodes recognised. These two metrics, time per task and errors in task completion, are generally accepted as metrics to evaluate the usability of an HCI (Nielsen, 2012).

Table 6-6: Number of inputs assessment.

	Total	Experienced
Expected Inputs	1560	390
Inaccurate Inputs	1053	112
Total Inputs	2613	502
Accuracy Rate	59.7%	77.6%

Table 6-7: Time assessment in second.

Total Time(sec)	Total Inputs	Time Per Input
7237	2613	2.76

As shown in Table 6-6, of 2613 number of inputs provided by the eight participants, 1560 were accurately recognised and 1053 were inaccurately recognised. The table also shows an accuracy of 77.6% has been achieved on input entry by two experienced participants, whereas all eight participants brought this down to 59.7% accuracy. Table 6-7 confirms that the MCIp was able to provide one input in 2.76 seconds on average when the MLU provides it with 25 rows of data per second (SRate of 40 *Hz*).

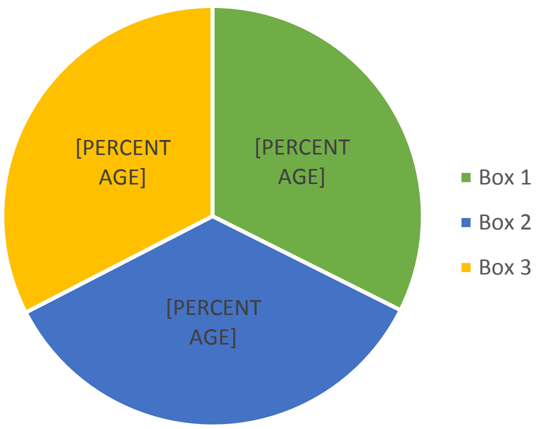


Figure 6-28: Number of inaccurate input prediction per box size.

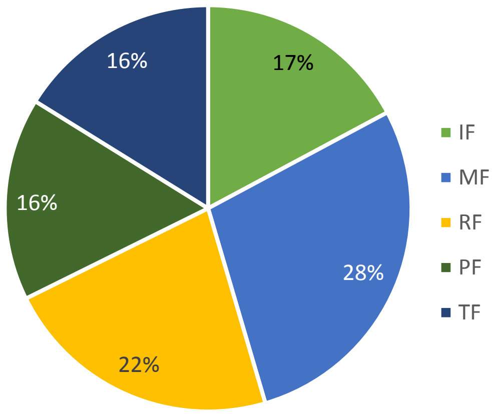


Figure 6-29: Gesture recognition inaccuracy based on each gesture.

Figure 6-28 represents the inaccuracy rate based on box dimension and weight. It can be concluded that changes in the box had no specific impact on the trend of prediction accuracy. In Figure 6-29 it is seen that the highest inaccuracies (28%) with predictions were observed while classifying the middle finger (MF) where the thumb and pinky fingers were recognised as highly accurate (16% inaccuracies).

Table 6-8 presents the information with regard to each individual participant and the metrics they are compared with, where participants are sorted by the degree of success per task. It must be noted that P1 and P2 are the two participants who had prior experience with the application of an MCI. Table 6-8 also highlights the two finger gestures the MCIp had the most difficulty in classifying, for each individual user. It is clear that these are always two adjacent fingers. The reason for this is the similarity of muscle group activities to form gesture for adjacent fingers.

Table 6-8: The participants' performance while inserting 15 EAN-13 barcode numbers.

	Average Time (Seconds)	Inaccurate Input	Inaccuracy Rate	IF	MF	RF	PF	TF
P1	42128.8	50	25.64%	32%	30%	14%	12%	12%
P2	45009.8	62	31.79%	35.48%	37.1%	16.13%	6.45%	4.84%
P3	57168.2	112	57.43%	10.71%	28.57%	44.64%	12.5%	3.57%
P4	57953.46	123	63.07%	4.88%	7.32%	8.94%	33.33%	45.53%
P5	63149	141	72.3%	24.82%	34.75%	17.02%	14.18%	9.22%
P6	62055.73	144	73.84%	7.64%	5.56%	9.72%	45.83%	31.25%
P7	73070.26	200	102.56%	29.5%	46.5%	14%	3%	7%
P8	81947.26	221	113.33%	9.05%	31.22%	38.91%	7.24%	13.57%

6.9.4 Evaluating the User Experience

Although evaluating the user experience was beyond the objective of the evaluation process, the participants were requested to complete a short survey (attached to Appendix B) after experimentation sessions to give their general experience of using an MCI in a daily life situation. Investigating their personal opinion of participation shows that, most of them had no problem with wearing the MYO Armband for a long time (each experiment took approximately an hour). A few participants, however, expected to be able to take off and put on the armband again and they found it irritating.

Users were prevented from recognising the system errors and their output was always confirmed as correct. After completing the tasks of the experiments, however, the general level of satisfaction with the error-free tasks was 42% on average. They had difficulty with filling an appropriate bar since the errors of gesture recognition were observable through the bars. They also believed that when the MCIp is compared with a fast HCI tool, it is only 32% as fast. The behaviour of the user can be accepted as normal when a device takes 2.76 seconds to provide an input.

6.10 Conclusions

This chapter tried to achieve the main and secondary objectives of this research study and tried to find answers for the fourth (*How can a sensory solution improve the current interaction techniques?)* and for the fifth (*How effective and efficient is the selected sensory solution?*) research questions. The proposed solution to the stated problem (Section 1.2) was to offer a prototype which used muscle-computer interfacing technique. Therefore, a MYO Armband was selected (Section 6.2) to acquire bio-signals using its eight built-in EMG electrodes from the forearm of a user to enable the prototype to recognise some specific finger-gesture movements (Section 6.5.1) of users which they could posture even if their hands were busy. Consequently, the discussions in this chapter explained the adequate knowledge acquired to design and develop the proposed prototype, and also to conduct the experiment to evaluate the solution.

The proposed prototype consisted of an Artificial Neural Network (ANN) to classify the processed bio-signals and extract features from the acquired bio-signals. The implemented network was modelled by using the Rprop training algorithm. In order to establish a tangible HCI, the MCIp used a web-based UI (Section 6.7.4) to provide feedback to users. In addition, it was able to log the EMG data as well as all the activities of users within the UI (Section 6.6.5). An experiment was then designed to measure and evaluate the performance of the prototype when it was employed in a real-world situation. The main reason for the evaluation was to investigate the weaknesses and strengths of the MCIp in the future (as will be discussed in Chapter 7). This information will help in the design process.

Two experiments were conducted initially to enable the prototype to perform satisfyingly. The first experiment was conducted to expose the behaviour of the gesture classifier ANN when it was constructed by different architectures. As the results presented in Section 6.9.1, a network with one layer between the input and output layers including 42 neurons, in addition to a bias neuron was appropriately modelled for the ANN classifier. The second experiment was conducted to investigate the effects of the Signal Processing and Feature Extraction techniques upon the data classification results Section 6.9.2. The results presented an optimised prediction by the data classifier ANN when the network was provided with a combination of all features extracted by the RMS, WL and matrix of convolutions from the EMG signals acquired by eight electrodes of the MYO Armband.

Two other experiments were conducted, first to measure the accuracy of data classification right at the output layer of the gesture classifier ANN (Section 6.9.3) and the second experiment was when the MCIp was used to recognise gestures and provide inputs at its UI (Section 6.9.4). The results from the evaluation of the gesture classification presented an accuracy of 34.87% by the ANN employed in MCIp.

Then, an accuracy of 59.7% was achieved on input entry by eight participants, whereas two experienced participants gained up to 77.6% accuracy after a 10 seconds training session for each gesture. The initial results indicate that the prototype can be used successfully to provide input to a computer system using an MCI. Also, a combination of the selected gesture-group (gesture-group II – Section 6.5.1) and the method of material handling was presented as a successful method by ignoring the non-stationary state of bio-signals.

The initial results indicated that the prototype can be used successfully to provide input to a computer system using an MCI. A combination of the selected gesture-group (gesture-group II – Section 6.5.1) and the method of material handling was also presented as a successful method which ignored the non-stationary state of bio-signals, however, it was restricted to handling materials with a specific dimension and weight. As another positive feature of the prototype exposed when the evaluation result of Experimentation-1 was compared with the results during the Experimentation-2. This could be seen that the smoothing the classification results within the MLU (Section 6.7.3) and UI (Section 6.7.4) had a significant influence on the gesture-recognition process as it had ignored possible inaccurate predictions from the classifier ANN.

As a conclusion, by considering the results of the evaluation and the knowledge which was acquired, additional research will be required to refine the current design of the solution. First, to enable the MCIp to provide inputs with the lowest possible number of errors in predictions and, second, to use the MCIp as a component within an existing HCI framework for ISs which aim at providing inputs into a real-world application such as the WMS or even a machine. In the following chapter conclusions and future research will be discussed.

Chapter 7. Conclusions and Future Research

Objective(s) of Chapter

1. *Outlining the achievements of this research study.*
2. *Identifying the IT-based artefact produced during the research study.*
3. *Identifying the knowledge-based artefacts acquired during the research study.*
4. *Highlighting the contributions of the research study.*
5. *Identifying future research.*

Structural Overview of the Chapter

Chapter 1: Introduction
Chapter 2: Research Design
Chapter 3: Warehouse Management and Automation Technologies
Chapter 4: Human Factors Involved in the Interaction with Warehouse Management Systems
Chapter 5: Sensory Technologies for Human-Computer Interaction
Chapter 6: Design and Evaluation of the Solution
Chapter 7: Conclusions and Future Research

7.1 Introduction
7.2 IT-Based Artefact
7.3 Knowledge-Base Artefacts
7.4 Critical Evaluation of the Current Prototype
- 7.4.1 Modifying the Machine Learning Unit
  - 7.4.1.1 The Training- Function
  - 7.4.1.2 The Error Rate
  - 7.4.1.3 The Training Strategy
- 7.4.2 Modifying the Signal Processing Unit
- 7.4.3 Modifying the User-Interface
- 7.4.4 Evaluating of the User Experience

7.5 Future Research to Refine the Prototype
7.6 Summary

7.1 Introduction

This research study used the DSR methodology to develop artefacts for the problem addressed in this research study (Section 1.2) which was:

> *The current sensory technologies used in a noisy warehouse environment create interaction problems with Warehouse Management Systems.*

As was identified in Section 1.2, the problem originated from a warehouse employee's action slip while performing a daily task using the Warehouse Management System (WMS). Another factor was the lack of communication between the user and the WMS in a noisy environment. Current HCI devices available on the market were being used but both hands of the user were busy. Consequently, to start the research project to address the main problem, the following thesis statement was formulated (Section 1.3):

> *A sensory technology, can be implemented and evaluated to improve the possible interaction with a Warehouse Management System.*

The main research objective originating from the thesis statement was to (Section 1.5):

> *To evaluate a selected sensory technology that could improve the interaction with a Warehouse Management System (ROM).*

This objective was mainly set to answer the main question identified in Section 1.4 as:

> *How can using a sensory technology improve the possible interaction with a WMS in a warehouse environment?* (*RQM*).

Then, after selecting the DSR research methodology for this study which was headed in Chapter 2, this dissertation was structured to gain the following secondary objectives:

> ***RO1:*** *Identify the latest automation technologies used in warehouse management.*
>
> ***RO2:*** *Identify human factors involved in performing daily operations in a warehouse.*

RO3: *Investigate available sensory technologies enabling human interaction with computer applications.*

RO4: *Select a sensory solution for improving interaction with a Warehouse Management System.*

RO5: *Evaluate the effectiveness and efficiency of the offered solution.*

Consequently, to highlight the relevance of the problem to the application domain and achieve the *RO1*, Chapter 3 explained how a warehouse was managed, the different resources in a warehouse, including people who might be faced with different problems and the latest automotive identification and communication technologies and techniques employed in the management of a modern warehouse.

To select an appropriate technology and to acquire the necessary knowledge about the problem in order to implement and evaluate a solution, Chapter 4 identified and described the human factors involved in the interaction with the WMS to achieve the *RO2*. The means to achieve the *RO3* introduced and described the modern sensory technologies available for the HCI which are applied to different application domains (Chapter 5). Chapter 5 also described the necessary procedures and techniques of an HCI tool using sensory technologies, specifically, the design and development of a direct neural interface (*RO4)* which must be applied. Chapter 6, in order to provide a practical solution which could solve the problem, described the selection and development of a prototype using the muscle-computer interfacing technique (MCIp) to achieve the *RO4*. In order to achieve *RO5,* Chapter 6 also discussed the experiment which was conducted to evaluate the MCIp by using certain statistical methods.

Chapter 7 identifies and presents the deliverables and contributions which were achieved during this research study and the future research. Therefore, in this chapter, the artefacts identified in Section 2.6, including an IT-based artefact (Section 7.2) and knowledge-based artefacts (Section 7.3) which were produced during this research project will be discussed.

The design of an HCI tool has specific requirements. The tool firstly must to be able to establish an error-free interaction within an appropriate time. Secondly, it must be able to be applied in a problem domain such as the existing problem identified in the providing inputs to a WMS (Section 1.2). In order to increase the efficiency of the

MCIp, Section 7.4.2 will highlight some Signal Processing and Feature Extraction techniques which may improve the performance of the SPU (Section 6.7.2). These techniques would extract more precise features, as Section 7.4.1 highlights some possible modifications to the application of an Artificial Neural Network (ANN) which may result in a more accurate classification of data and gesture recognition. To investigate the effects of these modifications, additional research and experimentations are required in the future.

In order to increase the effectiveness of the MCIp, Section 7.4.3 suggests a more effective UI design to be applied specifically to the interaction with the WMS in the future. In addition, a more precise evaluation of the experiments will be required to evaluate the MCIp to convert it into a completely user-friendly, effective, efficient and error-free solution as will be discussed in Section 7.4.4.

Section 7.5 will present future research by extending current experiments that were concluded in this research study (Section 1.6) and offers the design of a framework which is based on knowledge acquired during this research as the solution to overcome the main problem The proposed framework in addition to improve providing inputs hands full in a noisy environment, will also assist the user with his/her degree of attention while performing a task.

7.2 IT-Based Artefact

DSR methodology requires a research study to provide an actual artefact at the end of a research project which has to be evaluated to measure the product’s effectiveness on solving the problem. In addition, obtaining the *RO4 (Select a sensory solution for improving interaction with a Warehouse Management System)* encourages the research project to design and develop a practical solution using sensory technologies where to achieve *RO5 (Evaluate the effectiveness and efficiency of the offered solution)* requires performing an evaluation to expose the efficiency and effectiveness of the solution.

Therefore, as was explained in Chapter 6.2, in the design of the solution, the MCIp was proposed using a MYO Armband. The armband allowed the monitoring of the oscillatory activities of motor neurons in the forearm of the user. As no reports were discovered concerning the design and implementation of such an MCI in the literature, this research study was pushed to design such an MCI from scratch and investigate its eligibility of being considered as the solution to the main problem. Consequently, the MCIp was evaluated through experimentation with the aim of measuring its effectiveness and efficiency in solving the main problem[4].

The proposed architecture for the MCIp consisted of a number of different processing units which communicate with each other by supplying or consuming shared global variables which each of them shares. The MCIp also applies thread technology to enable parallel processing and independent performance in each unit. The units are:

1. ***EMGSPU:*** Acquires EMG signals from the MYO Armband.
2. ***SPU:*** Processes signals and extracts useful features.
3. ***MLU:*** Constructs a model for the ANN and labels EMG data with a gesture.
4. ***UI:*** Enables a user to interact with the system using web technology.
5. ***RGU:*** Logs the activities of each unit in a text file and in a spreadsheet.

A Feed-Forward Artificial Neural Network (FFANN) was trained by using the Rprop algorithm which was used to classify EMG signals acquired from the MYO Armband with the SRate of 40 *Hz*. The proposed Signal Processing and Feature Extraction techniques (which were selected in Section 6.5.3) improved the efficiency of the classification when the network was provided with a combination of different irrelative and correlative features. This result was observed in the experimentation explained in Section 6.9.2, when features from the RMS, WL and matrix of convolutions values were compared with each other. The implementation of correlative features influenced the classification results positively, when they were added to the popular and more commonly applied techniques.

The MCIp was evaluated by applying it to a manual barcode-entry-simulation task using the UI in experimentation sessions (Section 6.8) as well as some hands-free gesture posturing tasks. The techniques employed in feature extraction from the bio-signals and the classification of the hands-free finger-pinch gestures (as were depicted in gesture-group I in Section 6.5.1, Table 6-1) enabled the MCIp to achieve an average accuracy of 34.87% in test data collected during the Experimentation-1. When the MCIp was applied to a series of hands-full tasks using the hand-finger

[4] A conference paper submitted to SACSIT 2016 Conference is attached to Appendix J which also provides a summary of the procedures which were involved in the design, development and evaluation of the MCIp.

gestures (as were depicted in gesture-group II in Section 6.5.1, Table 6-1), the results of the evaluation presented the gesture-recognition success at a rate of 59.7%. However, entering each input into the system took an average time of 2.76 seconds.

The results from evaluating the user experience during the evaluation as well as, the performance of the MCIp presents it as a slow and not adequately accurate system which resulted in the user's dissatisfaction. It was also observed, however, in the general comments about the survey which each of the participants completed after the experiment that the participants expressed their experience of using an MCI as an interesting gesture-recognition technique.

Additionally, when the results of both experimentations (Experimentation-1 and -2) were compared, a positive influence of gesture-recognition strategy could be observed as the MCIp smoothed the results of the gesture-classifier right at the output layer of the ANN, when it was presented to the user via the UI.

The results acquired during the evaluation of the MCIp present the MCI as an economical, potential technology that can open a variety of applications within the HCI, and possibly in a warehouse environment it can be improved in different fields since it is an emerging technology. The MYO Armband is currently the only user-centred product commercially available on the market supporting MCI. The research study suggests that the MYO armband has the potential for input provision using MCI but future research is needed to improve the MCIp's accuracy. Section 7.4 will analyse the existing limitations in the design of the solution, and will suggest further future investigations.

7.3 Knowledge-Based Artefacts

During this research study, a variety of knowledge bases were acquired as the main and secondary objectives of the research, however, the initial scope was far too wide. As the DSR methodology assisted in the research project, the acquired knowledge has to cover the design, development, evaluation and refinement processes of the IT-based artefact, and further investigation is not necessarily required. However, the scope and limitations of this research project (identified in Section 1.6), restricted the design of the solution. Therefore, the sensory solution selected only partly addresses the existing problem by suggesting possible inputs to a WMS, and has limited application to solving the solution to either reduce or prevent the slip-of-action made by a worker. However, during the literature chapters, knowledge related to design and development for both problems was gained. In addition, a brief description of this knowledge is depicted in Appendix I. The following list expresses the knowledge acquired in this study, followed by the outline of achievements of the secondary research objectives.

1. ***RO1*** (*Identify the latest automation technologies used in warehouse management)**:***
   - The resources belonging to a warehouse (Section 3.3) include the physical space (Section 3.3.1), products, inventories (Section 3.3.2) and personnel (Section 3.3.4) were identified.
   - A WMS was identified (Section 3.4) as a necessary and effective element in the automation of warehouse management, which manages the daily operations by monitoring the processes (Section 3.4.2) and collecting the relative data.
   - The data types which are dealt with by the WMS were briefly pointed out during the identification of the resources in a warehouse.
   - Automated industrial vehicles (Section 3.3.4.3), storage and retrieval machines, (Section 3.3.4.4) were presented as equipment which handles the movement of materials between different areas of a warehouse automatically, without the involvement of manpower.
   - In Section 3.5, the barcode (Section 3.5.1), Radio Frequency tag (Section 3.5.3), magnetic stripe scanning (Section 3.5.4), Optical Character Recognition (Section 3.5.2), and machine vision (Section 3.5.5), were introduced as the popular techniques used to identify different resources in a warehouse.
   - The use of the Smart-Glasses in a Head-Up Display (HUD) system (Section 3.6.6) was introduced as the most efficient and effective technique when compared to other popular communication techniques, as discussed in Section 3.6. These other techniques include the lightening method (Section 3.6.3), Cart-Mounted Display (Section 3.6.4) and the use of the voice headset (Section 3.6.5).

- The HUD system uses AR technology and smart-glasses, which allow a user to interact with a system hands-free and eyes-free.

2. ***RO2** (Identify human factors involved in performing daily operations in a warehouse)**:***
   - In Chapter 4, an explanation of the central nervous system (Section 4.2), and of the physiological (Section 4.9) and biological behaviours of the human during interaction with the WMS was given.
   - Visual (Section 4.4) and auditory (Section 4.6) perceptions were introduced, as they enable a human to detect and perceive sound and light wave signals from the external environment, and the HUD system provides information to users through these communication channels.
   - Speech production (Section 4.5) and human movement (Section 4.9) were identified and described, as they enable a human to interact with the external environment. This interaction can include providing inputs to the WMS and handling materials in the warehouse manually.
   - Human attention (Section 4.7) was briefly described. A person's attention is necessary in the application of the WMS to perform and thus complete a normal task successfully, and as accurately as possible. Storage failures (performing a task multiple times), test failures (deciding to perform a task and doing something else), sub-routine failures (forgetting part of or mixing up the sequence of smaller actions within an action), discrimination failures (mixing up objects used for different purposes) and programme assembly failures (incorrect combination of actions), are some human errors which are a result of lack of attention (Section 4.7.2).
   - The relationship between human attention and the action of counting items was shown in Section 4.8. However, this counting action can be executed automatically, since the automaticity occurs after learning (Section 4.7.1). The process of counting was introduced in Section 1.2 as the most significant process in the warehouse management, where an error in an action impacted the quality of this counting process.
   - The anatomy of the forearm of the human was explained in Section 6.3, as the MCIp enables the HCI by detecting the neural activities within the forearm muscles. In addition, Section 6.4 identifies some factors which negatively impact the stationary state of the bio-signals acquired by an EMG.

3. ***RO3*** *(Investigate available sensory technologies enabling human interaction with computer applications)*:
   - The normal displays (Section 5.2.1), AR (Section 5.2.3), VR (Section 5.2.2), and some visual interface prototypes (Section 5.2.4), were introduced in Chapter 5 to describe the way in which an HCI system can provide visual feedback to users currently and in the near future.
   - Verbal interaction was introduced using the modern microphones and noise cancellation techniques, which included different software and hardware. In addition, the Whisper Audio chip was introduced as the latest piece of technology which is able to extract a spoken signal from a received sound signal. These technologies can be combined with the Automatic Speech Recognition (ASR) techniques in order to enable the HCI to use the verbal interaction ability of a user, even in a noisy environment (Section 5.3).
   - A text-to-speech technology was also introduced, as a method by which computer software synthesises a piece of text into an understandable sound wave. Normal computer speakers, and the bone conductors which transmit the vibrations from a sound signal directly into the inner ear, were introduced as technologies which enable auditory interaction between the user and a system (Section 5.4).
   - Image processing (Section 5.5.1), and the use of motion and orientation sensors (Section 5.5.2), were introduced as gesture-recognition methods. The motion and orientation sensors allow the detection of movement upon 6-Degree-of-Freedom (6-DoF), in the acceleration of an object in a three dimensional space, and in cardinal directions, where applying an image processing technique limits the movement of a user to a specific range of the image detector sensors.
   - Direct neural interaction with a computer was introduced using a brain-computer interface (BCI), and muscle-computer interface (MCI) was introduced in Section 5.6.
4. ***RO4*** *(Select a sensory solution for improving interaction with a Warehouse Management System)*:
   - The procedures necessary to design and develop a direct neural interface, which performs by detecting and recognising a specific behaviour within the nervous system, were identified in Chapter 5. The development of such an

interface requires, in the first place, the acquisition of bio-signals (Section 5.8). Secondly, when the signals have been smoothed, the features must be extracted from the signals, and finally the use of an ML technique is needed to establish the HCI (Section 5.9).

- The latest commercial EEG and EMG wearable technologies available on the market, are able to detect and monitor a specific series of nervous system activities, require less effort in programming, and have a user-centred design (Section 5.7). The EEG is able to detect sensory neurons and interneuron activities within the brain. These can be used in a design of a BCI. The EMG detects the activities of motor neurons in the muscles, which can be used in a design of an MCI.
- The different components necessary to construct an ANN, including the neurons, layers, connections, training algorithm and topology, were introduced.

6. ***RO5*** *(Evaluate the effectiveness and efficiency of the offered solution)**:***
   - The design and conducting of an experiment was discussed and explained during this section to provide a precise feedback which can be used in highlighting the positive and negative aspects of the MCIp.

7.4 Critical Evaluation of the Current Prototype

In addition to the knowledge base acquired during the study, other theories can be concluded and clarifying these theories requires more investigation of the experience gained in this investigation, but at this stage they can be used to refine the solution. These theories have originated from the weaknesses and strengths of the MCIp discovered after evaluating it. This knowledge can be applied both to refining the design, as well as, intensifying and enhancing its existing strengths.

When the results of the evaluation of gesture classification and recognition abilities of the MCIp were presented in Section 6.9, the inaccuracy of predictions was observed notably while classifying the EMG signals. This could be influenced by various criteria and the following sub-sections will formulate some hypotheses to investigate them in the future and remove the existing inaccuracy in predictions.

7.4.1 Modifying the Machine Learning Unit

As a component in the MLU, the process of the training-function was evaluated in Section 6.9.1 and the results were used to determine appropriate values for the necessary parameters to train a model for the ANN (Section 6.7.3). In the following sub-sections, a modification of these parameters is suggested which may increase the accuracy and performance of the MCIp.

7.4.1.1 The Training-Function

Figure 7-1 represents one portion of the value of the network's predictions as they are plotted with marked lines at the top as well as the amplitude value of eight (electrodes E1:E8) curved RMS features from the relax mode (P – RM). Pinching the index finger (P – IF three times) is presented by lines at the bottom (each peak represents one pinch). A desirable prediction would be recognised as a time when, for example, the network predicts the RM when there is no peak on signals or the peak is completely gone, as the muscles in this situation would be depolarised. But as can be seen, the network does not predict a uniform result and constantly labels data with IF. This can be a result of overfitting, as was identified in Section 6.6.3. The overfitting allows the network to memorise the entire given pattern as it has happened in this figure. A complete representation of this chart is presented in Appendix H.

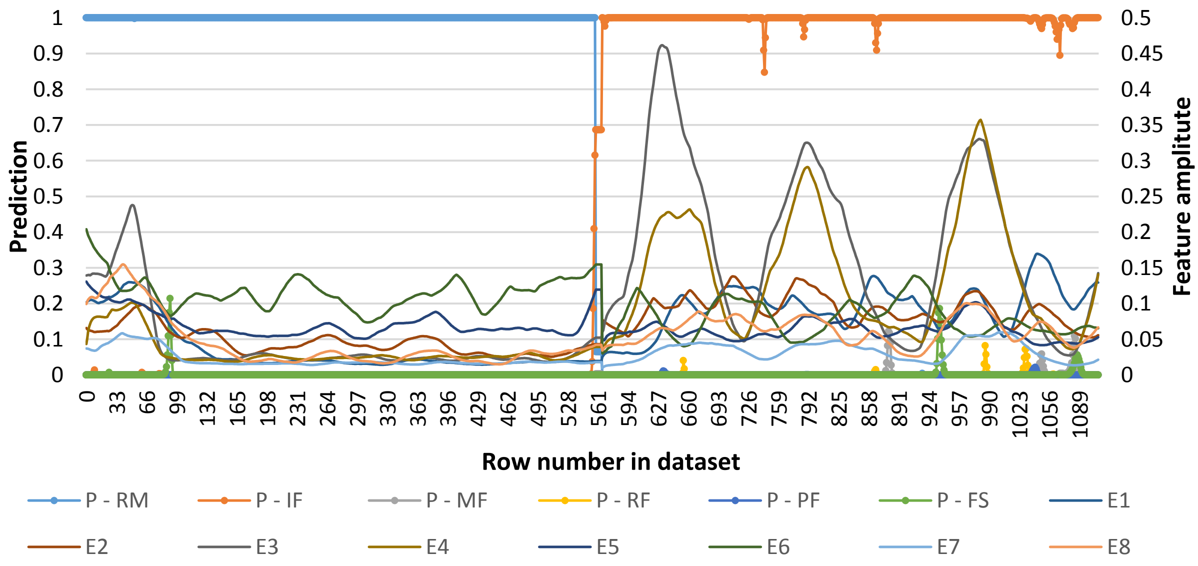


Figure 7-1: The accuracy of predictions of RM and IF for a given training dataset.

Modifying the strategy of configuring the ANN may solve the issue of inaccurate predictions by the network. A further investigation and experimentation must be conducted which separates the network for each gesture classification task and this may solve this issue. In other words, it may be better if the MCIp trains one network for each gesture separately. As it can be seen in the diagram in Appendix H, however, the results of the network's prediction may be accepted for the classification of the FS gesture. The network has memorised the rest of the training dataset while classifying other gestures. This shows that the network would behave differently when classifying each gesture in comparison with the other gestures. Consequently, the MCIp in the future, instead of having one network with a p number of neurons at the output layer, would have a p number of different networks with only one output. In this case, the network may require a setting of different values of the necessary parameters to construct different structures for each network which would be supposed to classify only one gesture.

7.4.1.2 The Error Rate

The selected value of 0.005% for freezing the iterations of the training algorithm may be a reason for the inaccurate prediction as well. A different error rate would be required to prevent the network from memorising an entire given dataset. This value might be different for each network when the MCIp follows the strategy planned in Sub-section 7.4.1.1.

7.4.1.3 The Training Strategy

A reason the MCIp could be a potential technology which deserves more investigation it is that the applied ANN was only trained with 10 seconds of pre-captured training dataset but it was still able to classify the gestures although with a low accuracy of predictions. Training a network with more given patterns may prevent the current inaccuracy (Section 6.7.3).

Applying continuous training will force the training algorithm to update the weights when the network is provided with a new pattern unfamiliar to the network. This may solve the problem and can be simply done by giving more tasks such as the tasks in the Experimentation-1 (Section 6.8.3) to present a continually growing training dataset. Employing another gesture-recognition device such as CyberGlove, Gest and Tap (Section 5.6.2) or even a piano MIDI controller can be used in the training of an MCI for the finger-gesture recognition. These devices can provide more accurate feedback of the hand-finger movements and a relatively useful feedback to the training algorithm. Once a desirable accuracy of gesture recognition is observed, the MCIp can be used without these devices.

7.4.2 Modifying the Signal Processing Unit

Table 6-4 (Section 6.9.2) reported on error rates when using the three individual features, the curved RMS, WL and matrix of convolutions, as well as a combination of the three features. The last column of the table provided an average error rate, indicating that a combination of the three features provides the best results when classifying gestures in the gesture-group II. The current inaccuracy of predictions could be caused by the complexity existing in the bio-signals (Section 6.4).

A hypothesis could be formulated with regard to this unit to increase the accuracy of predictions by applying other feature-extraction techniques to expose more precise and useful features. For example, features could be extracted by Integrated EMG, Variance of EMG, Willison Amplitude, Slope Sign Change, Histogram of EMG, Willison Amplitude and Zero Crossing techniques (Arief, et al., 2015; Chowdhury, et al., 2013; Phinyomark, et al., 2009, 2012).

The ANN applied to the MCIp, at the moment, is provided with only one row of data features which is exported from the top row in the Sliding Window (Section 5.9). Providing the network with the entire data in the Sliding Window may also influence the results of the prediction. It is possible that this idea will reduce the existing delay time in the gesture recognition as well.

7.4.3 Modifying the User-Interface

For the MCIp to be applied to an interaction with a WMS, it needs to cover the requirements of an HCI device for the WMS. This necessitates further research on the requirements of the WMS to acquire a greater knowledge base with regard to the design of such an application. For instance, data types, forms, navigations and other elements in the UI of the WMS would influence the design of a solution to enable the user to control and communicate with the WMS as efficiently and effectively as possible. The current design enables the user only to provide numeric datatype inputs by posturing the gesture which is encoded as a number.

7.4.4 Evaluating of the User Experience

An important factor that had a negative effect on the results from the evaluation was the usability of the MCIp. During the experimentation, action slips were observed multiple times by the researcher. This happened when the participant was requested to posture a specific gesture and he/she postured a wrong gesture. Observing and measuring these criteria were not considered during the experimentation and evaluation design. Therefore, the test dataset also contained uncertainty caused by posturing wrong gestures, whereas the MCIp had probably predicted the gesture accurately.

In addition, the results presented in Sections 6.8.1 and 6.8.2 highlight some challenges regarding the use of the MCIp as a successful, accurate and fast HCI tool. It was noted that experienced users had a much better accuracy rate than inexperienced users. Inaccuracy was observed less when the user had learned to interact with the system of using an MCI. These criteria were not taken into consideration while designing the experimentation.

Tan, Tan, Mok, Goh, et al. (2015), as well as, Mars and Abbey (2010) suggested short term meditation as a positively influencing factor which reduces the non-stationary state of bio-signals generated by the human brain. In this study it was found that the participants did not concentrate on performing a biological activity (moving muscles) on purpose. A reason for the success of experienced participants was their prior knowledge of how the MCIp learns from them, and how it picks a specific behaviour out of their biological activities.

7.5 Future Research to Refine the Prototype

In order to refine the design and achieve an appropriate solution for solving the main problem in the future, a framework can be designed and developed as is depicted in Figure 7-2. The proposed design may cover both the existing problem occurring during the provision of input and the slips of actions while performing tasks. This will require adequate investigation and evaluation of the framework as well.

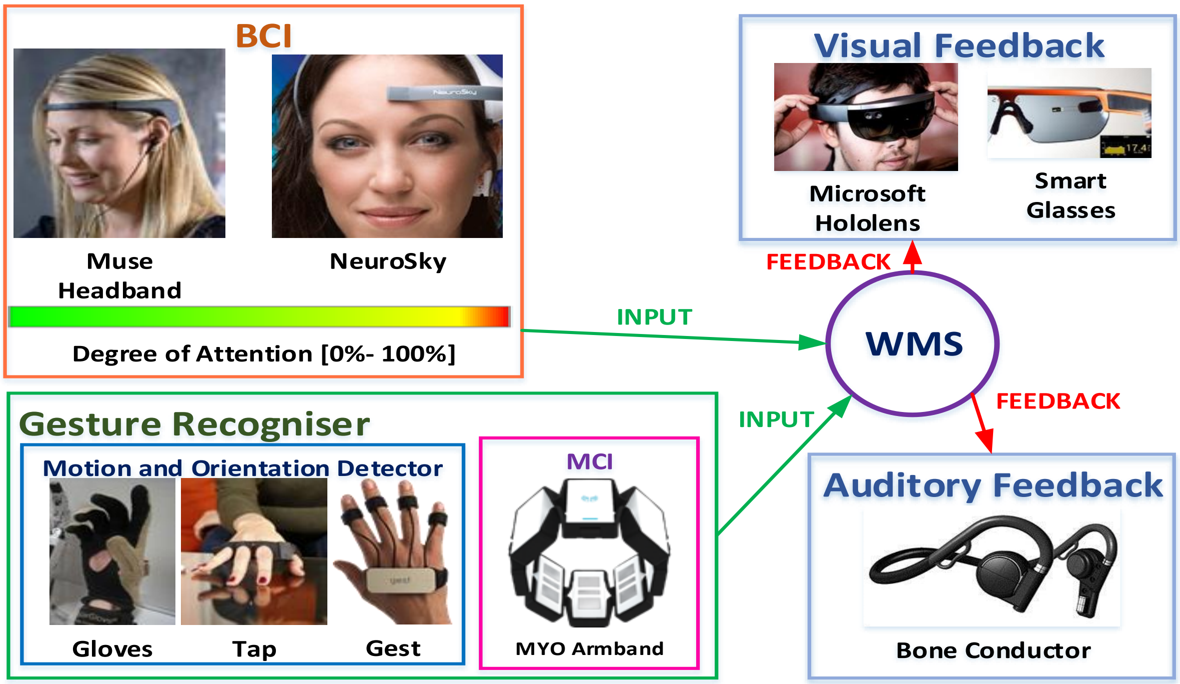


Figure 7-2: A proposed framework to be designed to solve the main problem.

As it can be seen in Figure 7-2, a BCI, as a component in the framework can provide a visual and/or auditory feedback to a user in proportion to the degree of their concentration on a specific task. Feedback may help the user to remain concentrated on a task. During this research study an appropriate knowledge-base with regard to human attention and the development of a BCI was acquired, however, more investigations will be required.

Within the suggested framework, a method of gesture interaction was selected to enable a user to provide inputs into the WMS. Although, Gest and Tap are not commercially available on the market yet, unlike to bio-signals, the signals received from these devices are stationary and do not have the complexity existing in the bio-signals. In addition, there are some possible applications but a user may have difficulty using these devices. For example, a surgeon in a surgery or a musician who plays guitar requires more freedom for his/her hands and fingers. In some similar cases, the application of MCI and a MYO Armband is a better preferred option, but as was explained in Section 7.4, the hand-finger gesture recognition using the MYO Armband still requires improvement and future investigation.

7.6 Summary

As the main problem in this research study stated, the current sensory technologies used in a noisy warehouse environment create interaction problems with Warehouse

Management Systems. Therefore, the stated aim of this research project was to offer a solution to the problem:

> *A sensory technology, can be implemented and evaluated to improve the possible interaction with a Warehouse Management System.*

The problem basically occurred during interaction with a WMS in a noisy warehouse environment when using the current HCI sensory technologies in interaction with a WMS. The primary investigation in the literature presented no report of an appropriate solution to this problem. Consequently, the Main Research Objective (*ROM*) in this study was:

> *To evaluate a selected sensory technology that could improve the interaction with a Warehouse Management System.*

This chapter described the artefacts which contributed to this research study followed by the *ROM*. The Design Science Research (DSR) regulates the research to iterate the three main cycles with the aim of introducing the environment within the Relevance Cycle in which the problem was identified. These are, acquiring a knowledge-base which is essential to assist design and development within the Relevance Cycle, and the Design Cycle which applies the information gathered in the other two cycles to the process of design, development and evaluation of the solution. The DSR methodology directs the study into more iterations of the three cycles to refine the design of artefacts which can be confirmed by analysing the results of the evaluation of the design. The final products of such a research project would be IT-based and knowledge-based artefacts which respectively provide an actual and theoretical artefact which aims to solve the problem.

Section 7.3 introduced the IT-based artefact produced in this research study, which was Muscle-Computer Interface prototype (MCIp) whose purpose was to enable a user to provide numeric inputs into a system using a MYO Armband. In Section 7.4, the results of the evaluation of the current IT-based artefact were interpreted to initiate more iterations and refine the design of the designed prototype until it become an accurate, error-free and working solution. The aim was to modify the current techniques applied to the different components within the MCIp. This can be achieved by modifying the applied ANN for gesture classification (Section 7.4.1), applying other Signal Processing and Feature Extraction techniques (Section 7.4.2), modifying the UI (Section 7.4.3) and finally, evaluating the prototype by considering more aspects (Section 7.4.4).

The knowledge-based artefacts produced at the end of this research project were identified in Section 7.3 and included theories to explain different aspects of the requirements to design a solution. Although, the design of the IT-based artefact was restricted to use an MCI only to solve the existing problem, by providing inputs, and the literature chapters, in addition to the introduction of other sensory technologies, a wider range of theories and knowledge base concerning the development of a solution to prevent or reduce slips of action of users were also investigated and discussed. Various theories were discussed which could even be used in the design of a total solution using a BCI as well as motion and orientation sensory devices. More than adequate knowledge and information was acquired during this research study which can lead to future research in order to integrate some of the sensory technologies which were introduced and construct a comprehensive solution to the main problem.

The last section (Section 7.5), took one step beyond the scope and limitations of this research study, and offered a framework for a solution which can be designed and developed to deal with the problem in the future. This requires more iterations upon the design, rigor and relevance cycles continuously.

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Appendix A: University Ethics Clearance

Nelson Mandela Metropolitan University

for tomorrow

• PO Box 77000 • Nelson Mandela Metropolitan University
• Port Elizabeth • 6031 • South Africa • www.nmmu.ac.za

Chairperson: Research Ethics Committee (Human)
Tel: +27 (0)41 504-2235

Ref: [H16-SCI-CSS-002/Approval]

Contact person: Mrs U Spies

28 June 2016

Prof A Calitz
Faculty: Science
South Campus

Dear Prof Calitz

A SOLUTION FOR WAREHOUSE MANAGEMENT SYSTEMS USING SENSOR TECHNOLOGIES

PRP: Prof A Calitz
PI: Mr S Zadeh

Your above-entitled application served at Research Ethics Committee (Human) for approval.

The ethics clearance reference number is **H16-SCI-CSS-002** and is valid for three years. Please inform the REC-H, via your faculty representative, if any changes (particularly in the methodology) occur during this time. An annual affirmation to the effect that the protocols in use are still those for which approval was granted, will be required from you. You will be reminded timeously of this responsibility, and will receive the necessary documentation well in advance of any deadline.

We wish you well with the project. Please inform your co-investigators of the outcome, and convey our best wishes.

Yours sincerely

CB Cilliers

Prof C Cilliers
Chairperson: Research Ethics Committee (Human)

Appendix B: Biographical and User Experience Questionnaire

Biographical information		
Age	○	**18-25**
	○	**25-30**
	○	**30-35**
	○	**Over 35**
Gender	**Male** ○ **Female** ○	
Race	**African** ○ **Asian** ○ **Black** ○ **Coloured** ○ **White** ○	

User Experience Questionnaire

How did you experience the wearing of the device?

How do you rate the accuracy of your task performance?

Erroneous	1	2	3	4	5	Error-free

How do you rate the speed of using the MYO Armband to capture data and provide system input?

Slow	1	2	3	4	5	Fast

What other interaction device(s) do you prefer to use in order to insert inputs when your hands are busy?

What is your general experience with the use of sensory devices (e.g. for playing games)?

Appendix C: Information and Informed Consent Form

NELSON MANDELA METROPOLITAN UNIVERSITY

INFORMATION AND INFORMED CONSENT FORM

Title of the research project	**The Selection and Evaluation of a Sensory Technology for Interaction in a Warehouse Environment**
Reference number	
Principal investigator	**Seyed Amirsaleh Saleh Zadeh**
Address	
Postal Code	
Contact telephone number (private numbers not advisable)	

A. DECLARATION BY OR ON BEHALF OF PARTICIPANT		**Initial**
I, the participant and the undersigned		

A.1 HEREBY CONFIRM AS FOLLOWS:		**Initial**
I, the participant, was invited to participate in the above-mentioned research project		
that is being undertaken by	Seyed Amirsaleh Saleh Zadeh	
from	Department of Computing Sciences	
of the Nelson Mandela Metropolitan University.		

THE FOLLOWING ASPECTS HAVE BEEN EXPLAINED TO ME, THE PARTICIPANT:					Initial
2.1	**Aim:**	The investigators are studying and evaluating the use of different sensory technology in interaction with a Warehouse Management System The information will be used to/for research purposes.			
2.2	**Procedures:**	I understand that the experiment will take a maximum of 30 minutes.			
2.3	**Risks:**				
2.4	**Possible benefits:**	As a result of my participation in this study, interaction with a computer using muscular activities could be established			
2.5	**Confidentiality:**	My identity will not be revealed in any discussion, description or scientific publications by the investigators.			
2.6	**Access to findings:**	Any new information or benefit that develops during the course of the study will be shared as follows:			
2.6	**Voluntary participation / refusal / discontinuation:**	My participation is voluntary	YES	NO	
		My decision whether or not to participate will in no way affect my present or future care / employment / lifestyle	TRUE	FALSE	

3.	No pressure was exerted on me to consent to participation and I understand that I may withdraw at any stage without penalisation.	

4.	Participation in this study will not result in any additional cost to myself.	

A.2 I HEREBY VOLUNTARILY CONSENT TO PARTICIPATE IN THE ABOVE-MENTIONED PROJECT:			
Signed/confirmed at		on	20
Signature or right thumb print of participant	Signature of witness:		
	Full name of witness:		

B. STATEMENT BY OR ON BEHALF OF INVESTIGATOR(S)									
I,	(name of interviewer)				declare that:				
1.	I have explained the information given in this document to				(name of patient/participant)				
	and / or his / her representative				(name of representative)				
2.	He / she was encouraged and given ample time to ask me any questions;								
3.	This conversation was conducted in	**Afrikaans**		**English**		**Xhosa**		**Other**	
	And no translator was used <u>OR</u> this conversation was translated into								
	(language)	by	(name of translator)						
4.	I have detached Section D and handed it to the participant		**YES**		**NO**				
Signed/confirmed at			on		20				
Signature of interviewer			Signature of witness:						
			Full name of witness:						

C. DECLARATION BY TRANSLATOR *(WHEN APPLICABLE)*			
I,	(full names)		
ID number			
Qualifications and/or			
Current employment			
confirm that I:			
1.	Translated the contents of this document from English into	(language)	
2.	Also translated questions posed by	(name of participant)	as well as the answers given by the investigator/representative;
3.	Conveyed a factually correct version of what was related to me.		
Signed/confirmed at	on	20	
I hereby declare that all information acquired by me for the purposes of this study will be kept confidential.			
Signature of translator	Signature of witness:		
	Full name of witness:		

D. IMPORTANT MESSAGE TO PATIENT/REPRESENTATIVE OF PARTICIPANT

Dear participant/representative of the participant

Thank you for your/the participant's participation in this study. Should, at any time during the study:

- an emergency arises as a result of the research, or
- you require any further information with regard to the study, or
- the following occur

(indicate any circumstances which should be reported to the investigator)

Kindly contact	
at telephone number	(it must be a number where help will be available on a 24 hour basis, if the research project warrants it)

Appendix D: Written Information Given to Participant Prior to Participation

Written Information Given to Participant Prior to Participation

Dear Participant,

You have been selected to take part in the research study carried out by Seyed Amir Saleh Saleh Zadeh. The study is being conducted to evaluate a sensory technology while interacting with a Warehouse Management System (WMS). This can be carried out with providing inputs to a semi-simulated WMS electronic form using a MYO Armband.

The researcher will provide you with relevant information describing the purpose of the study as well as your rights as a participant in this study. You will be expected to follow the training session and follow the instructions as is required in picking task list. You are then expected to provide feedback after each unit as to what your perceptions and opinions are regarding the usability of the tool. The duration of the experiment will take a maximum of 30 minutes of your time.

Please feel free to ask questions at any time. If at any time during the evaluation, you wish to withdraw, you are welcome to do so. If any problems arise during the evaluation, please report them to the researcher immediately. The researcher will be present at all times. Feedback will be request by completing two questionnaires. You will be required to complete four tasks in a maximum time of 30 minutes.

This study has been approved by the Research Ethics Committee (Human) (REC-H) of the Nelson Mandela Metropolitan University. The REC-H consists of a group of independent experts that has the responsibility to ensure that the rights and welfare of participants in research are protected and that studies are conducted in an ethical manner. Studies cannot be conducted without REC-H's approval. Queries with regard to your rights as a research subject can be directed: *Research Ethics Committee (Human), Department of Research Capacity Development, PO Box 77000, Nelson Mandela Metropolitan University, Port Elizabeth, 6031.*

Your identity data will remain confidential at all times; however, you might be referred to as "participant X". This research may be presented at conference proceedings or journals. If at any time you feel uncomfortable you have the right to withdraw from the study with no penalty or loss of benefits.

Yours sincerely,

Seyed Amir Saleh Saleh Zadeh

Researcher and Evaluator

Appendix E: Oral Information Given to Participant Prior to Participation

Nelson Mandela Metropolitan University

for tomorrow

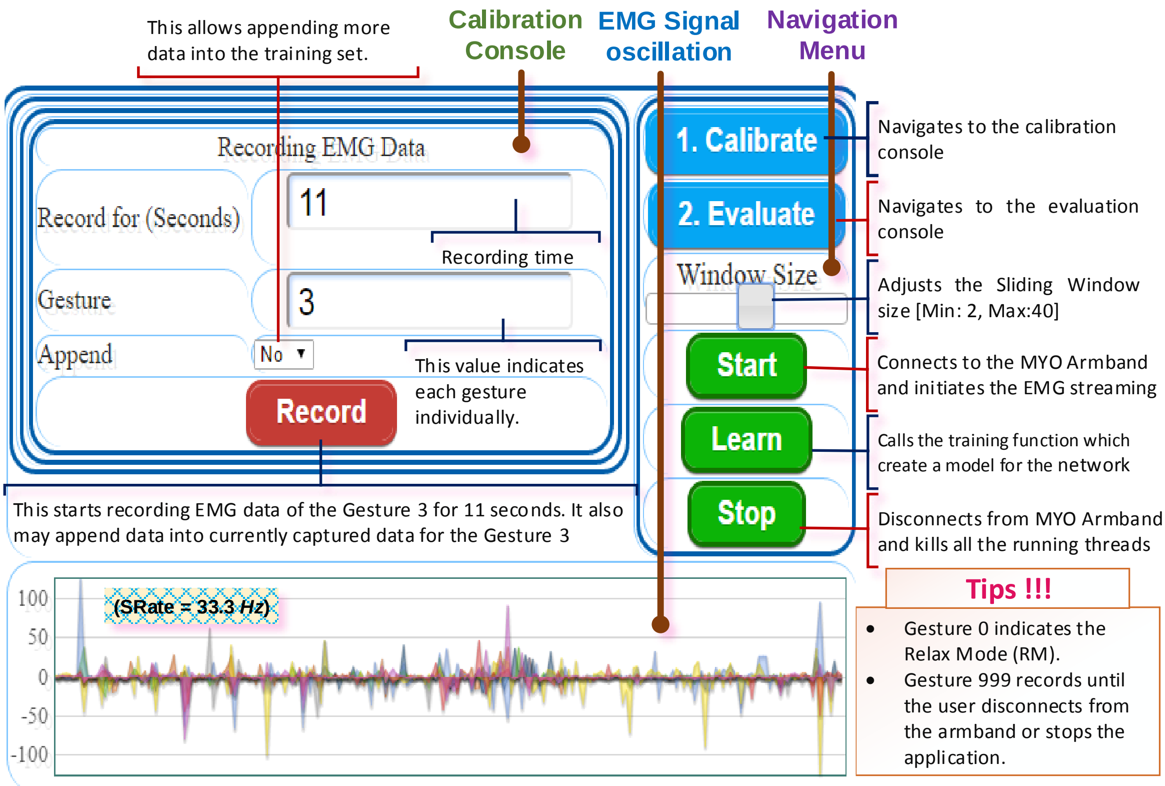
Oral Information Given to Participant Prior to Participation

I, Seyed Amir Saleh Saleh Zadeh, the Primary Investigator (PI) and Researcher will provide participants with an oral introduction. The introduction will be given in English and will include:

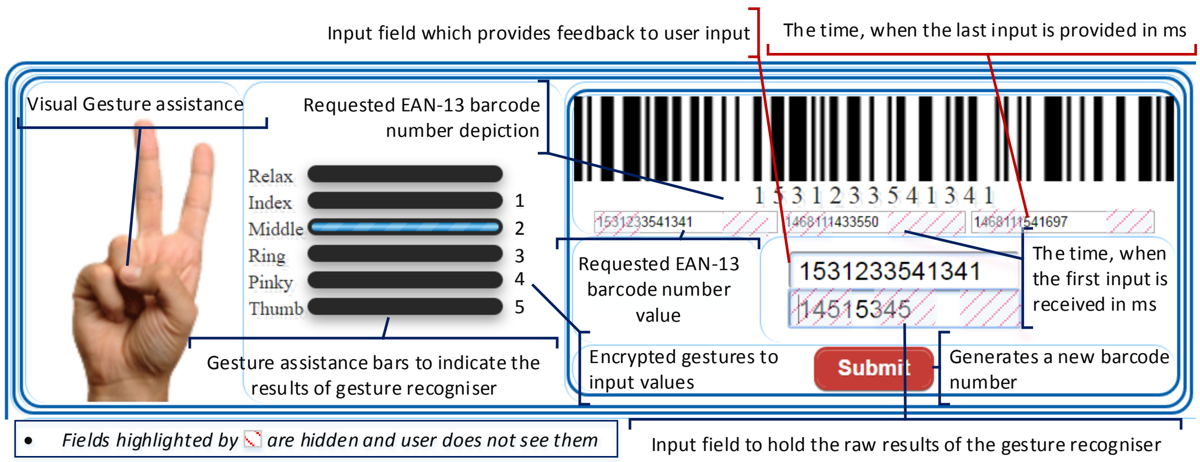
- The participants' rights will be given to them, indicating that they are free to withdraw from the study at any time.
- The purpose of the system that the participants will evaluate as well as the purpose for the evaluations.
- Participants will be made aware that all the results from the evaluations will be used for academic purposes only.
- What is expected from the participants during the evaluation. This includes the signing of the consent form (Appendix C), an oral and written (Appendix C and Appendix D) introduction to the evaluation, completion of the biographical form and the post-task questionnaire.
- The basic system functionality will be explained and participants will be given a chance to familiarise themselves with the system and performing tasks.
- Any questions the participants might have will be answered orally by the PI.

Appendix F: The User-Interface of the Proposed Muscle-Computer Interface Prototype

Main screen and calibration console screen shot



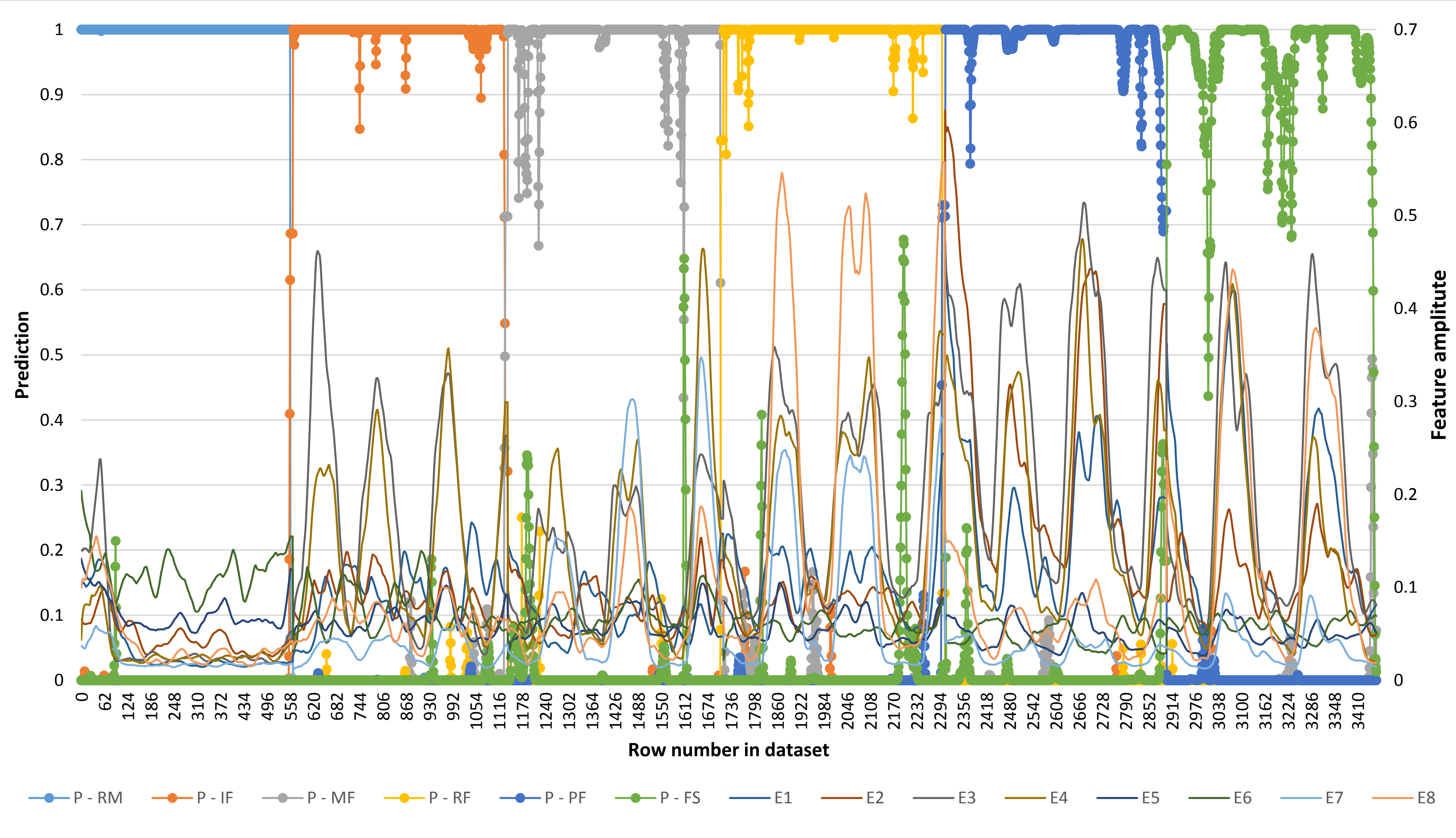
Evaluation console screen shot



Appendix G: The RMSE and the MVP Values for the Predictions of the Training and Test Datasets

			P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*Avg.*
RM	Training	RMSE	0.0914	0.0204	0.0247	0.0963	0.1195	0.0352	0.0806	0.0498	**0.0647**
		AC	99.81%	99.75%	99.75%	93.94%	96.30%	99.31%	94.47%	98.65%	**97.75%**
	Test	RMSE	0.5102	0.5987	0.5862	0.7407	0.5715	0.7408	0.7755	0.7434	**0.6959**
		AC	46.42%	49.02%	7.61%	52.45%	27.47%	10.98%	13.73%	38.72%	**30.80%**
IF	Training	RMSE	0.1247	0.1296	0.0838	0.0430	0.0935	0.2187	0.1948	0.1138	**0.1427**
		AC	89.71%	94.25%	97.20%	98.32%	94.04%	71.56%	87.73%	89.78%	**90.32%**
	Test	RMSE	0.6824	0.5987	0.6053	0.5277	0.5037	0.4256	0.6301	0.4173	**0.5489**
		AC	28.88%	49.02%	8.20%	47.83%	9.48%	16.07%	25.93%	46.88%	**29.04%**
MF	Training	RMSE	0.0525	0.1303	0.0887	0.0850	0.0711	0.0503	0.0813	0.0922	**0.1389**
		AC	99.91%	94.25%	97.28%	94.69%	96.92%	98.67%	94.26%	94.31%	**96.29%**
	Test	RMSE	0.4671	0.3414	0.5743	0.3508	0.3922	0.4906	0.3562	0.4289	**0.4252**
		AC	45.89%	49.15%	26.37%	53.00%	20.80%	8.14%	11.40%	35.76%	**31.31%**
RF	Training	RMSE	0.0085	0.0270	0.0814	0.0826	0.0684	0.0268	0.2821	0.0687	**0.1859**
		AC	99.99%	99.54%	97.31%	96.93%	95.45%	99.56%	96.89%	96.01%	**97.71%**
	Test	RMSE	0.5706	0.3393	0.4905	0.4190	0.3382	0.2445	0.3581	0.3741	**0.3918**
		AC	37.79%	42.82%	49.82%	56.61%	35.22%	33.50%	40.51%	42.23%	**42.31%**
PF	Training	RMSE	0.1958	0.0348	0.0979	0.0442	0.0345	0.0339	0.3001	0.0560	**0.1222**
		AC	82.42%	99.15%	95.64%	98.14%	99.12%	99.31%	86.97%	98.78%	**94.94%**
	Test	RMSE	0.5206	0.4747	0.2897	0.4877	0.3056	0.3946	0.3434	0.4024	**0.4023**
		AC	44.12%	38.99%	33.08%	43.22%	35.09%	35.62%	40.75%	40.51%	**38.92%**
FS	Training	RMSE	0.0218	0.0287	0.0574	0.0848	0.0190	0.0189	0.0349	0.0512	**0.0671**
		AC	99.98%	99.96%	97.76%	92.96%	99.77%	99.80%	95.06%	98.14%	**97.93%**
	Test	RMSE	0.5306	0.3542	0.4426	0.4004	0.5794	0.3662	0.4439	0.4768	**0.4493**
		AC	49.47%	48.25%	22.54%	46.16%	9.18%	25.04%	38.74%	55.23%	**36.83%**

Appendix H: The Accuracy of Predictions for a Given Training Dataset



Appendix I: Deliverables of the Research: Knowledge-Base and IT-base Artefacts

Design Science Research

CH01

Problem Identification: *The current sensory technologies used in a noisy warehouse environment create interaction problems with Warehouse Management Systems.*

Thesis Statement: *A sensory technologies, can be implemented and evaluated to improve the possible interaction with a Warehouse Management System.*

Main Research Question How can using a sensory technology improve the possible interaction with a WMS in a warehouse environment?

Main Research Objective To evaluate a selected sensory technology that could improve the interaction with a Warehouse Management System.

Environment

CH03 ***Warehouse Management***

Resources: Space, Product, Personnel and Equipment

Automation Equipment: Automotive material handling vehicles; AS/RS; WMS; and Automatic Identification and Communication Equipment

Automation Methods: Barcode/RF Scanning; Cart-mounted Display; Ligthening; and Head-Up Display.

In a semi-automate warehouse management:

1- **HUD:** **Least amount of errors; High-speed performance; Hands-free; Eyes-free; Does not perform in noisy environment;**

2- **Voice Headset:** **Hands-free; Eyes-free; Error-prone; Low-speed performance; Does not perform in noise;**

3- **Hand-held Scanners:** **Performs in noisy environments; Hands-busy; Eyes-busy; Error-prone; Low-speed performance;**

Relevance Cycle

CH01
CH02
CH03 → RO1
CH07 → ROM → DELIVERABLES
CH04 → RO2
CH05 → RO3 RO4
CH06 → RO4 RO5

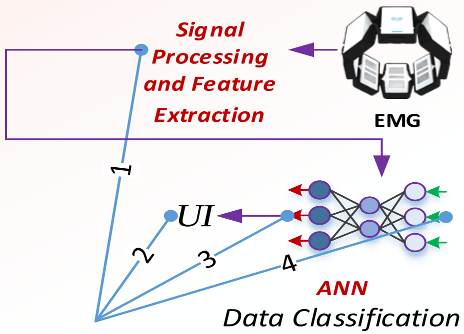
Design

Design Cycle

Rigor Cycle

CH06 ***Design and Evaluation***

Extreme Programming Software Development



Evaluation Experiment

1- Signal Processing and Feature Extraction techniques Selection

2- The performance of gesture recognition (59.7%)

3- The accuracy of predictions (34.87%)

4- The construction of the ANN

Knowledge Base

CH04 ***Human Factors***

Senses and Perception

Human Vision; Auditory Perception; Speech Production; Human Movement; Attention; Action Slips; Counting Action;

EEG Technique: to monitor the neural oscillation from the brain.

EMG Technique: to monitor the neural oscillation from the muscular system.

Bone Conduction Technique: to enable a direct auditory interaction with the inner ear

CH05 ***Sensory Technologies for HCI***

Visual Interaction
Augmented Reality; Virtual Reality;

Verbal Interaction
Microphones; Noise cancellation techniques; ASR;

Auditory Interaction
Bone conductor; Text-to-Speech technology;

Gesture Interaction
Image Processing (restricted area of detection)
Motion and Orientation Sensors : Accelerometer; Gyroscope; Compass; Bend Sensor; Soli; Detectors with user-centred design (AcceleGlove; CyberGlove; Muse Headband; Gest; MYO Armband;)

Direct Neural Interaction
1- Bio-signal acquisition (MYO Armband; Muse Headband; Neurosky;).
2- Signal Processing and Feature Extraction Techniques;
3- Machine Learning techniques;

CH06 ***Design and Development***

Human Factors: Anatomy and physiology of the forearm.

Feature Extraction Technique: Root Mean Square; Wavelength; Matrix of convolutions.

Machine Learning Technique: Supervised learning data classification technique; Feed Forward Artificial Neural Network; Resilient backpropagation technique to model the network.

UI: to give feedback to user. **Log Management:** to collect data of user activities within the prototype

Appendix J: SAICSIT 2016 Conference Paper – An Evaluation of a Neural Network Based Human Muscle-Computer Interface using a MYO Armband

ABSTRACT
In recent years, Human Computer Interaction (HCI) has become an important field of study as it has improved human performance while interacting with computerised systems. The increasing diversity of bio-sensing and wearable technologies on the market today have allowed researchers to design more efficient, effective and fully natural User-Interfaces (UI) such as a Muscle-Computer Interface (MCI) and a Brain-Computer Interface (BCI). MCI and BCI have been used for various purposes, such as controlling wheelchairs, piloting drones, providing alphanumeric inputs and improving the performance of athletes.

In this paper, the application of biomedical signals (bio-signals) in HCI is discussed by introducing an MCI prototype (MCIp) which enables a user to provide muscle-computer input empty-handed or when carrying an object. The MCIp applies a Feed Forward Artificial Neural Network to classify features extracted from the surface Electromyography (EMG) signals acquired by a MYO armband around the user's forearm. In the current state of development, an accuracy of 59.7% has been achieved on input entry by eight participants, whereas two experienced participants gained up to 77.6% accuracy within a 10 seconds training session for each gesture. The initial results indicate that the prototype can be used successfully to provide MCI input to a computer system.

Categories and Subject Descriptors
- **Human-centred computing → Human-computer interaction (HCI) Interaction techniques → Gestural input.**
- **Computing methodologies → Machine learning → Machine learning approaches → Neural networks.**

Keywords
Muscle-Computer Interface; MYO Armband; Gesture Recognition.

1. INTRODUCTION
The effective management of a warehouse environment can open new opportunities for industries operating in global markets [1]. Warehouse and logistic systems are being designed and automated, in order to achieve more effective operational management and increased productivity and competitiveness in the supply chain. This is achieved through reducing processing time and costs [2]. Organisations are increasingly striving to shift daily routine tasks towards automated systems, due to increased personnel costs [3], humans being error-prone and time consuming labour practices [4]. Current material handling and transport automation technologies such as smart robot fleets [5], automated guided vehicles [6] and drone delivery system prototypes [7] have been implemented to counter the lack of human ability to handle the different processing of items between the different members in the value chain [4, 8].

In recent years, industry has focussed increased attention to the semi-automated management of daily operations by using sensory technologies. Table 1 and Table 2 compare the most popular and modern identification and communication technologies employed

Table 9: HCI tools vs solutions

	HF	EF	WiN
H-H BC/RF	✗	✗	✓
CMD	✗	✗	✓
VP	✓	✓	✓
HUD	✓	✓	✗

Table 10: HCI tools performance

	SPd	Ac
H-H BC/RF	Low	Med
CMD	Med	Low
VP	Low	Low
HUD	High	High

in semi-automated warehouse and logistics systems: Handheld Barcode/Radio Frequency (H-H BC/RF) scanners, Cart-Mounted Display (CMD), Voice picking (VP) and Head-Up Display (HUD) – which uses smart-glasses and augmented reality. Table 1 presents the abilities of a worker when he/she uses the technology to perform a task not requiring the use of their hands (HF for hands-free); not requiring eye tracking (EF for eyes-free) and working in a noisy environment (WiN). Table 2 indicates the degree (low, medium and high) a specific technology can perform a functionality quickly (SPd) and collect data accurately (Ac) [4, 9].

Hands-full (carrying an object) and eyes-busy handling operations are known as factors impacting the effectiveness and efficiency of manual task performance [10]. In addition, the worker spends a considerable amount of time each day interacting with a system using handheld devices. On the other hand, a noisy workplace environment, is known to be a major factor that causes disturbance of speech communication [11]. Initial costs and poor communication performance in noisy environments have reduced the popularity of HUD in industry. Kopin Co. [12] introduced the Whisper audio chip that can be combined with smart-glasses as a solution to this problem. There is, however, still no product on the market equipped with this chip. The Whisper chip applies a novel noise cancellation technology and voice extraction filter by acoustically modelling the environment around the user to recognise speech in any noise level even when the user speaks with a low or normal voice.

Brain-Computer Interfaces (BCI) and Muscle-Computer Interfaces (MCI) have been reported in recent studies as technologies offering different solutions to this problem. Wand and Schultz [13] present an MCI for speech recognition which classifies acquired surface-EMG signals from potential articulatory muscle activities and translates them into text even when the subject speaks in a noisy environment. Other MCIs have presented the potential of being a robust technique for HCI, by using surface EMG. Chen, et al. [14] used surface EMG electrodes to recognise the activity of a specific muscle group when the user makes a gesture by the flexing of each individual finger. Researchers at the Backyard Brains Institute have classified EMG signals from different finger and wrist movements by placing 5 EMG electrodes on the forearm of the user in order to control a robotic hand [15].

At a deeper bio-signal interaction level, Suppes, et al. [16] have introduced a BCI which recognises unspoken words by classifying features extracted from Electroencephalograph (EEG) and Magnetoencephalography (MEG) signals generated by the user's brain when it imagines speaking a word. During the last decade, this approach has been improved by researchers by applying more advanced feature-extraction and pattern- recognition techniques, as well as by adding other stimulation techniques such as Visual Evoked Potential [17, 18].

Through research the potential of BCI and MCI as commonly approved interaction tools, has been identified. They still, however, have a long way to meet a normal user's expectations of an easy-to-use HCI tool. The available EEG devices in the market that can be used in designing a BCI for a normal user (such as NeuroSky [19], Muse Interaxon [20], Emotiv Epoc and Insight [21]) have not extended their abilities further than measuring the user's concentration, specific feelings, emotions and some states of mind [22]. The first and only available surface EMG device, at a reasonable price in the market, which can be used in an MCI is the MYO Armband from Thalamic Labs which is a mobile motion, orientation and muscle sensor [23].

In this paper, the authors present their knowledge gained while designing and developing an MCIp using the MYO armbands. Results of conducting various experiments using these armbands are provided. In Section 2, background literature related to the design of the MCIp is given. Section 3 describes the modular architecture of the MCIp. Components that are discussed, include the EMG signal service provider (3.1), signal processing unit (3.2), machine learning unit (3.3), UI (3.4) and report generating unit (3.5). The conducted experiment to evaluate the MCIp is discussed in Section 4, while Section 5 interprets the results and Section 6 reports on the strengths and weakness of the MCIp.

2. BACKGROUND AND RELATED WORK

This section provides an overview of related work regarding the design of the MCIp, by investigating the source of the bio-signal (2.1), acquiring bio-signals by using EMG techniques (2.2) and the way these signals can be interpreted (2.3).

2.1 Bio-Signal Source

When the decision is made to move a particular limb, the brain processes the decision within the cerebellum located in lower area of the brain (below the pons) and creates an appropriate command. A motor neuron is a type of nerve cell which is responsible for carrying out this specific type of command by electrical impulses [24] through the spinal cord and nervous system to a related muscle group [25]. The electrical impulses are generated when a neuron inside the nervous system performs a "spike" to communicate with other neurons within its neighbourhood. The spike occurs when a neuron charges and discharges itself by opening and closing the Sodium+ and Potassium+ ion channels in the neuron membranes [26]. In the muscular system, a muscle, in response to a spike, performs changes over its length and size. These changes enable a physiological body movement when a muscle attached to bones and joints with tendons, is simulated [27].

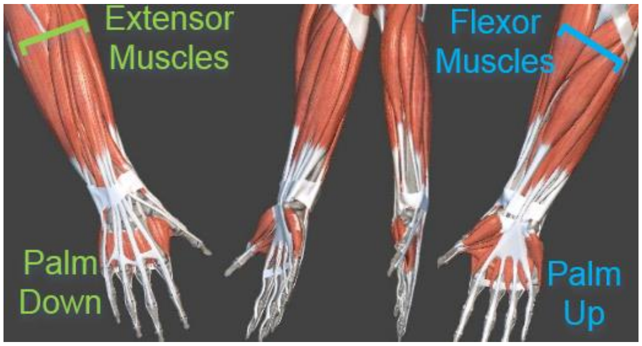


Figure 1: The muscles in a human's right-hand forearm

In the same way, limbs on the body like hands, fingers and wrists, can be moved by following a variety of postures. For example, limbs can be flexed, extended, abducted or circumducted. Each of these movements involve a different muscle group, in different ways. **Figure** presents the composition of muscles in the forearm which enable the wrist and the fingers of the hand to be moved. By adjusting their length each tendon connected to the fingers can move. Dr. Hal Blumenfeld explained this complicated process in his book [28] and a summary is provided by Blumenfeld [29].

The activity in muscles become more complex, when for example, a flexion occurs by bending, making a fist, gripping, grasping or folding the fingers. The flexion is handled by the flexor muscle group (**Figure**). Muscles within this muscle group behave differently depending on each movement style [28].

2.2 Electromyography (EMG)

The spike of a motor neuron generates a tractable electrical signal over time which discloses its activity in varying degrees through the neuromuscular system [26]. A specific intercommunication of a group of neurons generates a specific oscillatory activity. Communication between neurons can give rise to a different frequency in oscillations in comparison with the spike frequency of individual neurons [30].

EMG is a procedure which assesses the activities of the motor neurons and muscles by receiving neural oscillation signals from invasive (where the electrode is implanted directly into a muscle tissue) and non-invasive (where the electrode is placed on the surface of skin just over the muscle tissue) EMG electrodes. It converts the signals into either a graph (**Figure 3**), sound or numerical values in order to interpret them [31].

The EMG signal is known in literature as a nonstationary and complex signal since its velocity can be easily impacted by a wide variety of variables. These include the amount of body fat, hair, the size/shape of muscles, the amount of stress on muscles, age, gender, hydration and random physical conditions. This makes the signal complex, requiring a great amount of effort to process and interpret [32, 33].

2.3 Bio-Signal Based Human Computer Interface Design

The design and development of a bio-signal-based HCI, with the aim of classifying and recognising a specific biological behaviour, necessarily pursues the following steps:

1) Bio-signal acquisition using a bio-sensor (as it was discussed in Section 2.2);
2) Processing the acquired signal;
3) Extracting features from the signal;
4) Applying a Machine Learning(ML) technique to classify the features; and
5) Recognising a behaviour.

The term signal processing refers to using mathematical, statistical and computational techniques [34] to smooth, minimise or remove noise. These filtering techniques aim to minimise the complexity of data, which facilitates the discovery of useful knowledge from a dataset [34, 35]. The extracted, explicit features are used as input data for a Machine Learning (ML) technique. By using Artificial Intelligence (AI) a system is enabled to learn by applying different techniques from different paradigms [36].

Data classification is a popular ML technique which, as its name implies, discovers useful knowledge by classifying and labelling data. This technique allows the extraction of useful features from the bio-signal data and the classification of specific behaviours of bio-signals [37]. Georgoulas et al. [38] discuss and suggest a few techniques involved in data classification such as Support Vector Machines, Decision Trees, and K-Neural Networks, which can be applied for the classification of bio-signals [27, 39]. Artificial Neural Network (ANN)s are also reported frequently by other researchers as successful and powerful data classifiers which have been applied on bio-signal-based data classification [40, 41, 42, 43, 44].

3. ARCHITECTURE DESIGN AND DEVELOPEMENT

After a number of different architecture were tested, an appropriate architecture (Figure 2) was designed and implemented (using the JAVA programming language), which satisfied the needs and expectations for the proposed MCI making use of the MYO armband. The architecture consists of a main engine which includes an EMG Service Provider (EMGSPU), a Signal Processing Unit (SPU) and a Machine Learning Unit (MLU). A Report Generating Unit (RGU) and a User-Interface (UI) which communicates with the system through a web service (WS) were also included.

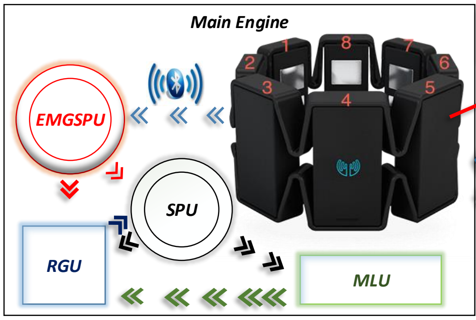


Figure 2: Proposed Architecture for the MCIp using a MYO Armband

3.1 EMG Service Provider Unit (EMGSPU)

The MYO armband used is equipped with eight EMG electrodes located around the forearm muscles, and outputs a raw EMG signal. The Sample Rate (SRate) of the EMG signal is 200 Hz, streaming 8 channels (E1:E8) of 8-bit data through a Bluetooth 4.0 low energy USB to a computer [45]. Figure 3, for example, presents the raw EMG data captured from electrodes 3, 4 and 5 in 1.43 seconds when the user presses the ring finger on a surface.

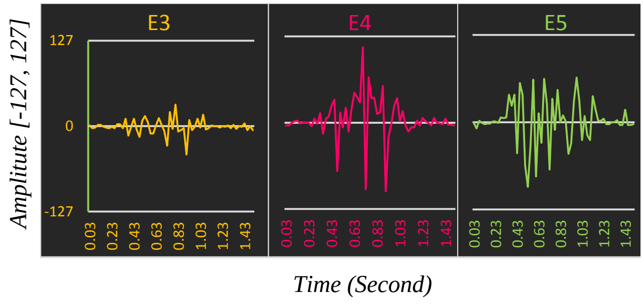


Figure 3: The raw EMG signal captured by MYO in 1.43 seconds (SRate of 40 *Hz*)

The MYO armband is equipped with internal software which classifies wrist gestures and provides filtered and processed signals from EMG electrodes and other built in sensors. In addition, there is a variety of open-source libraries available in different computer programming languages that reduced the amount of effort during the development phase [46].

The EMGSP acquires signals for the MCIp from the MYO with a SRate of 40 *Hz*, by using an infinite running thread. Reduction of the sample rate reduced the amount of received data while giving a 25 milliseconds (ms) time to the system for further data-preparation processes.

3.2 Signal Processing Unit (SPU)

The main objective of the SPU is to increase the efficiency of knowledge discovery by improving data quality and removing or reducing the available noise in the data.

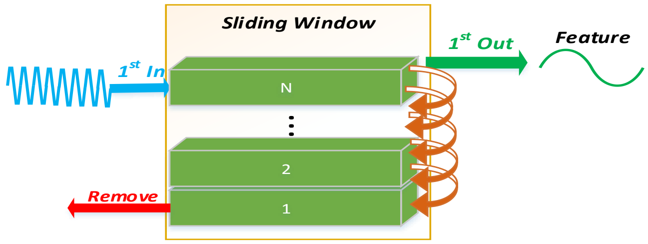


Figure 4: The structure of the sliding window

Figure 4 presents the structure of a sliding window used in the SPU. The sliding window is an allocated chunk of memory with the size of *N* data rows which holds data in it and allows time-series data to slide through it, while processing the data it holds inside. When the EMGSP fires for the first time, it takes *T* ms to fill the window and export the first row of completely processed data where:

$$T = N * \frac{10^3}{SRate} \qquad (1)$$

The SPU receives raw signals from the MYO armband, and is responsible for extracting features from data inside the sliding window. Before extracting the features, data noise need to be reduced using normalisation (Section 3.2.1). The first feature is extracted by using a Root Mean Square (RMS) mechanism (Section 3.2.2). This feature is smoothed and curved (Section 3.2.3). Additional features extracted from the curved RMS feature, are Wavelength (WL) value (Section 3.2.4) and a correlative feature is extracted by measuring the value of convolution between signals (Section 3.2.5).

3.2.1 Min-Max Scaling Normalisation

In order to reduce the inconsistency in data and to bring all values into a specific range the value of X' can be measured by:

$$X' = a + \frac{(X - X_{min})(b - a)}{X_{max} - X_{min}} \tag{2}$$

Where a and b are arbitrary values to limit the range [47].

In order to ignore data which may present no muscular activation with their poor value, a and b forms a limited range between 75% and maximum value of the ascending sorted values in the sliding window (**Figure 5**).

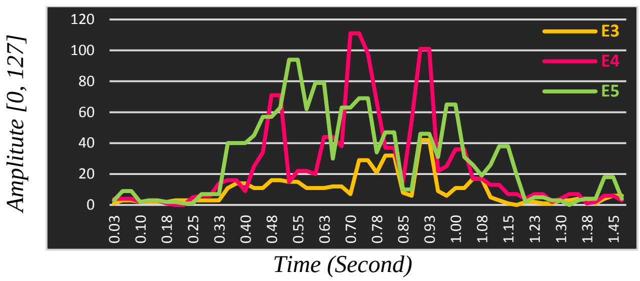


Figure 5: Normalised value by min-max scaling function

3.2.2 Sliding Root Mean Square

A one-dimensional feature is extracted by measuring the Root Mean Square (RMS) value of the normalised values in the sliding window [48]. The RMS value is given by:

$$RMS = \sqrt{\frac{\sum_{k=1}^{k=n} x_k^2}{n}} \tag{3}$$

The RMS value extracts an envelope from the raw signal. **Figure 6** depicts RMS features, extracted from raw signal presented in **Figure 3**.

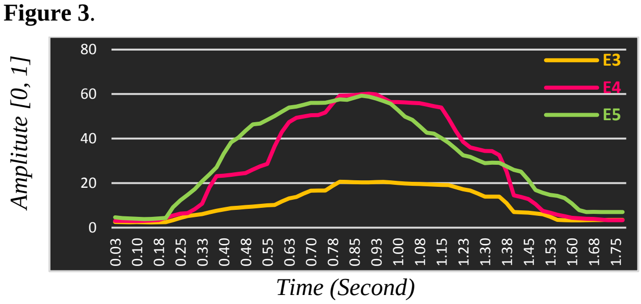


Figure 6: Extracting the envelope from raw EMG data by measuring the RMS value of data in the sliding window

3.2.3 Polynomial Curve Fitting

This function fits a curve on a data series by assuming the data series as a function of $f(x)$ [49] where:

$$f(x) = m_k + \sum_{k=1}^{k=n} m_k\,(x^k) \tag{4}$$

The MCIp implemented the Apache Math Utilities library for Java [50] to calculate the value of this function and smooth the RMS feature as shown in **Figure 7**.

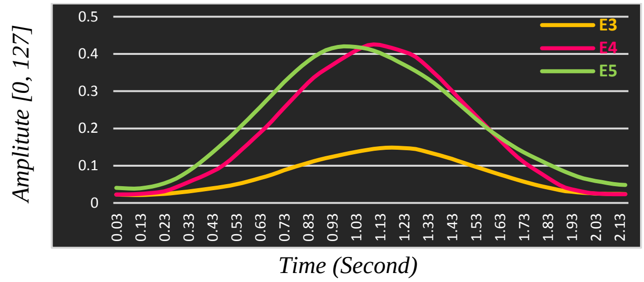


Figure 7: Polynomial curve fitting to smooth the RMS feature

3.2.4 Wavelength (WL) Value

The WL value measures the complexity of the EMG signal [35] and can be calculated by:

$$WL = \sum_{K=1}^{k=n} |x_{k-1} - x_k| \tag{5}$$

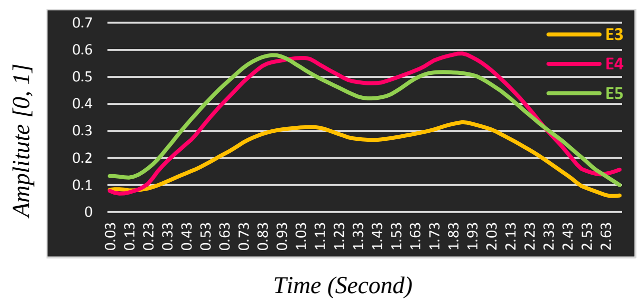


Figure 8: The wavelength of the curved RMS features for electrodes E3:E5

The WL value extracts extra features from the RMS value as it is presented in **Figure 8**.

3.2.5 Correlative Feature: Discrete Convolution

Figure 9 depicts two different gestures postured by the middle and ring finger while pressing a long time on a surface. As it can be observed, the data of all electrodes look almost the same. However, E3, E6 and E7 can be identified as classifying factors. When polarising and depolarising the muscle, the classifier may be confused by the similarity of both gestures in some points. This is identified as a Conflict Point (CP).

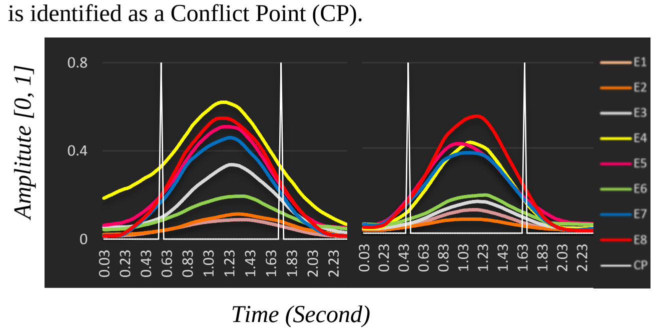


Figure 9: A comparison between two smoothed RMS features while pressing on a surface for a long time with two different individual fingers (2.23 seconds)

In order to address the above mentioned conflicts, additional features can be extracted, by applying discrete convolution. This implies implementing cross-correlation between individual signals. This generates an *n-by-n* triangular matrix of M_{Correl} where *n* is the number of electrodes. M_{Correl} can be defined as:

$$M_{Correl} = \begin{bmatrix} 1 & x_{E1:E2} & x_{E1:E3} & \cdots & x_{E1:E8} \\ & 1 & x_{E2:E3} & \cdots & x_{E2:E8} \\ & & 1 & \cdots & \vdots \\ & & & \ddots & x_{E7:E8} \\ & & & & 1 \end{bmatrix} \quad (6)$$

The number of features can be extracted by M_{Correl} for *n* number of electrodes is measured by *N* where:

$$N = \frac{n^2 - n}{2} \quad (7)$$

A discrete convolution is a mathematical way of combining two finite data series to form a third signal [51] and is measured by:

$$Conv(x) = \sum_{k=0}^{k=M} f[k].g[x-k] \quad (8)$$

where *M* is the number of data in both *f* and *g*. The feature is then extracted from the average value of all of the computed convolution values by:

$$Feature_{Conv(x)} = \sum_{k=1}^{k=M} Conv(x) \quad (9)$$

Figure 10 presents simulated signals generated by the function convolution between signals received from E3:E5.

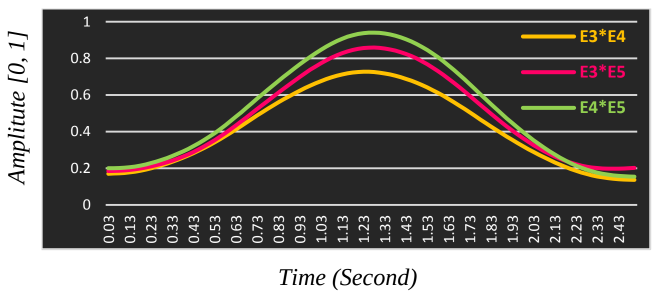


Figure 10: Features extracted by function Conv(x) from electrodes E3:E5

3.3 Machine Learning Unit (MLU)

The MLU can be defined as the brain of the MCIp which learns the user's specific forearm muscular behaviours when it postures a gesture during a calibration (learning) session. It models the calibration data, and evaluates the EMG data stream by determining the probability of the data belonging to a specific class.

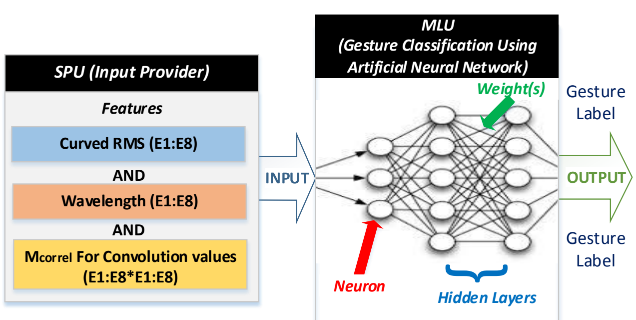


Figure 11: The layout of the MLU

As it is depicted in Figure 11, the MLU receives the following features from the SPU: curved RMS features for each 8 electrodes (Section 3.2.3), WL values for each 8 curved RMS feature (Section 3.2.4) and 28 Convolution Signals (Section 3.2.5) as shown in formula 7. It then classifies them via an Artificial Neural Network (ANN).

Basically ANNs are based upon an interpretation of the biological neural network function as it was discussed in Subsection 2.1. In an ANN, a neuron (also called a perceptron) can be viewed as a processing unit with limited resources. The neuron is able to connect and communicate with other neurons by a well-determined spike. It, however, makes, disrupts and strengthens these connections during the learning phase. Artificial neurons receive inputs from cells in their neighbourhood through connections that are weighted. An activation function in the ANN fires a perceptron when it is assigned with a value of 1, and it will be off in any other state by being given a 0 [52]. ANNs can differ from each other by the learning paradigm that modifies the weights of the connections, the composition of connections between the different layers, and the activation function [53].

A Feed Forward Artificial Neural Network (FFANN) has been frequently reported as a powerful classifier technique in classifying features in bio-signals. The FFANN directs the data flow from the input neurons directly forward through the neurons within hidden layers to the output neurons. In the FFANN there is no cycle between different neurons in the network [41, 43, 44].

A Backward Propagation of Errors (Backpropagation) is a popular ANN training method. Resilient backpropagation (Rprop) is considered the best algorithm, measured in terms of convergence speed, accuracy and robustness with respect to training parameters. Learning in Rprop involves multiple iterations (each called an epoch) in the network by updating connection weights by processing each piece of data, based on the amount of error in the output compared to the expected result [54]. In many applications, the FFANN applies a sigmoid function as an activation function which shapes a sigmoid curve (**Figure 12**) and can be defined by the formula:

$$S(t) = \frac{1}{1 + e^t} \quad (10)$$

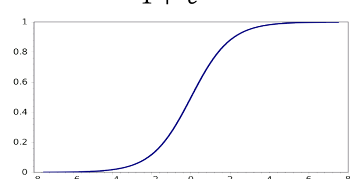


Figure 12: Sigmoid S shape curve

The MCIp constitutes an FFANN with *I* number of outputs, where *I* is the number of gestures the network would be requested to classify.

In order to apply the MCIp in the real-world and establishing effective HCI, the MLU receives a stream of data from the SPU continuously and asks the ANN to label it. The highest value firing output node indicates the label of class the incoming data belongs to. The MLU receives $10^3/EMG_{Srate}$ lines of data in one second which may either contain an inaccurate or accurate prediction if we determine a node with the highest value as the classification result. To smooth incoming results and ignore uncertain recognitions, an array rates a recognised label and the un-rating of other labels with giving each label a value between the range $[0, Sliding\ Window\ Size]$. Then, the MLU streams this

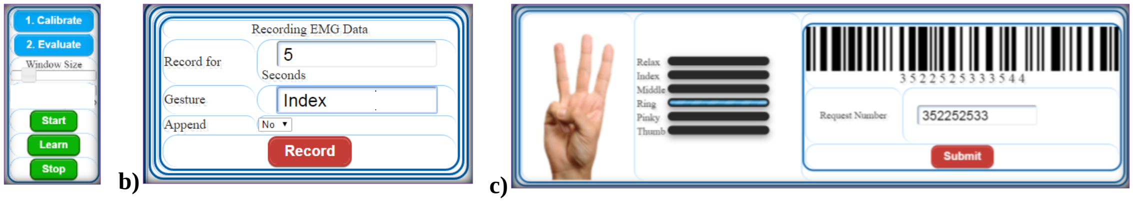


Figure 13: Screenshots from the User-Interface of the MCIp. a) The menu. b) Gesture calibration: collecting data for the training the model. c) Gesture assistance and barcode entry

array by

providing a global variable.

The Encog Machine Learning framework was used that allowed for the training and creation of the FFANN by using its multi-thread processing ability and Rprop capabilities [55].

3.4 User-Interface

The MCIp allows users to interact with the system through its built-in web-based UI which communicates with the main engine using AJAX technology. The main engine provides access to different functionalities or values of variables with a JavaScript Object Notation Web-Service Protocol (JSON-WSP) web-service as its gateway.

The UI allows the user to:

1- Select either calibration or evaluation, start or stop the armband, calibrate the MCIp and change the sliding window size using the menu (**Figure 13**.a).
2- Create or append a training dataset for one gesture in a gesture-group by giving it a specific name, for a specific duration of time in seconds (**Figure 13**.b).
3- Give feedback to the user in order to express the current state of gesture recognition (**Figure 13**.c).
4- Allow the user to enter the given barcode number provided on the screen, using finger gestures (**Figure 13**.c).

The UI receives the array of predictions from the MLU and presents it to the user via a percentage in the bars (**Figure 13**.c). To make sure that the user intends a gesture certainly, when a bar fills from 0% to 100%, the UI selects it as the desired input and immediately prevents providing any other before the user fills the relax mode bar with 100% value.

3.5 Report Generating Unit (RGU)

The main aim of the RGU is to collect, manage and archive the raw EMG data of a user's activities in the text format with the aim of conducting further analysis on the data. In general, the activities include calibration and task completion.

On completion of the calibration stage, this unit evaluates the generated network by feeding it with the entire training dataset again. Then, it generates a spreadsheet and reports the results of the evaluation. The report includes the training dataset, ideal values and the predicted values.

4. EVALUATION EXPERIMENT

We conducted an experiment to observe and measure the performance and efficiency of the MCIp while it was being applied on the HCI, using a hands-full scenario.

4.1 Participants

A group of eight participants with no muscular or skin condition were used. These were volunteer students (4 females and 4 males). Two participants had prior experience with using an MCI and the others were novices.

4.2 Setup

The MYO armband was fitted over the participant's forearm muscles of the dominant hand, directly below the elbow. For the entire duration of the experiment, the armband had to fit comfortably. It was furthermore checked that it was not too loose so that it would not slip around the forearm when the participant moved his/her hands nor if it were struck by an object. The participants were requested to prevent slight movements of the armband.

4.3 Design

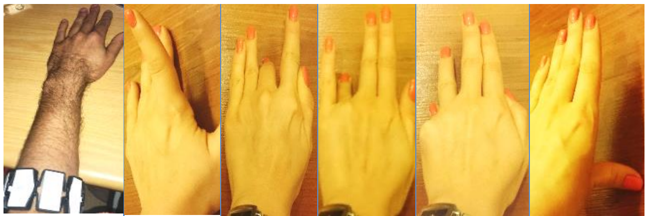
The experiment was conducted in two phases. Firstly, by measuring the performance of the machine-learning technique applied within the MCIp and secondly by measuring the efficiency of the MCIp when it was applied on a real-world problem. Before starting a session, the MCIp was calibrated with 6 modes, including each finger gesture, as well as a relax mode.

4.4 Gesture-Group Selection and Material Handling Method

When an MCI is performed in a real-world situation, it has to recognise whether the user makes a gesture, or does not make it. This is essential to prevent inaccuracy of the gesture classification and increase the accuracy of gesture recognition. Some particular application domains require just-in-time response which might influence the favourability of this interaction technique. Even in application domains that do not require just-in-time response, such as providing alphanumeric inputs, the existence of this limitation results in inaccurate results. This could, for example, occur when the user flexes the middle finger and then shifts to the flexion of ring finger. In this case the muscles pass through an intermediate state (as it was described in Section 2.2 and depicted in **Figure 9**), which may impact the result of gesture recognition [27, 56].

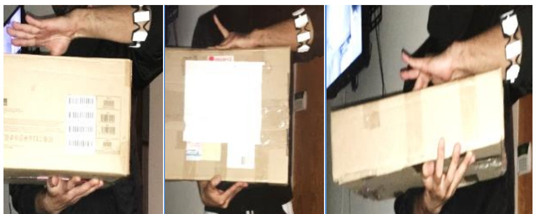
Instead of designing and offering a complicated computational solution to measure and influence variables on EMG signals, we used a customised gesture-group (**Figure 14**) and introduced a change in the method of handling materials (**Figure 15**). As is depicted in **Figure 15**, in this method, the participant was required to hold and lever the box by putting one hand under the load and using the surface of box as an armrest for the input-generating hand. In this way, the participant was able to hold the box in a stable position.

The customised gesture group includes applying pressure on a surface for a long time (an approximate amount of 600 ms) with



Armband's Placement and Relax Mode (RM)	Index Finger (IF)	Middle Finger (MF)	Ring Finger (RF)	Pinky Finger (PF)	Thumb Finger (TF)

Figure 14: Selected gestures within the gesture-group



	Box 1	Box 2	Box 3
Dim:	*38*32*25 (Cm)*	*40*13*40 (Cm)*	*40*40*13 (Cm)*
Weight:	*2.7 Kg*	*1.2 Kg*	*1.2 Kg*

Figure 15: Manual material handling method and hands placement (dimensions: Width * Length * Height in centimetres, and weight in Kilograms)

the middle, ring, pinky and thumb finger. The index finger gesture would be postured by extending the finger.

4.5 Procedures

During the calibration time, the participant was requested to sit on a chair with his/her back in a supported position with his/her forearm lying down at a tangent to the surface of a table with the edge of the table positioned closely to the armband (**Figure 14**. Armband's placement and relax mode). This could reduce the tension in the forearm muscles. The participant was requested to perform gestures in this position. We captured EMG signals for each gesture for 10 seconds when the participant was continuously pressing/extending the gesture for about 1 second and then relaxing muscles for 1 second (approximately 3 positions were captured for each individual gesture).

Three different box sizes were selected (Figure 15), based on the fact that the participant does not feel tension or frustration when he/she holds a box. We requested the participants to stand up straight and hold each box in both hands while completing the tasks. The MCIp generated an EAN-13 barcode number (digits ranged between 1 and 5 since only one hand was used) presented on a large-size screen and the participant was required to use the MCIp input method to insert five different barcode numbers within each task. Each gesture was encoded as one digit.

When the participant had provided one input by making a gesture, the MCIp did not allow him/her to make any other inputs before the participant released the tension from the muscle group activated in the previous gesture by trying to stay relaxed for about one second and letting the muscles be depolarised. Then, the system enabled input to be received again. Saponas et al. suggest a similar methodology [27, 51].

4.6 Evaluation

The most popular techniques suggested by literature to evaluate an ML system suggest evaluating an applied ML algorithm with both the data used for the training process as well as data recorded when the algorithm is involved in a real-world situation during the experiment.

Firstly, the performance of the modelled FFANN was evaluated when it was being provided with features identified in Section 3.2 extracted from the training dataset. To measure the accuracy of the ML, we trained the FFANN with each feature separately and evaluated the model by measuring the Root-Mean-Square Error (RMSE) which explores the accuracy of a prediction by representing the differences between the expected and predicated values for a given set of inputs. The RMSE value for a dataset with the size of n containing predicted values of p and expected values of e is computed by the formula [57]:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{k=n}(|p_k - e_k|^2)}{n}} \quad (11)$$

Secondly, to keep the user motivated while collecting data for the evaluation of the MCIp's general efficiency, the user was always provided with feedback that the entry was correct even when it was incorrectly recognised. The raw result of the gesture recognition was, however, logged and used for evaluation. Efficiency was measured by recording the time taken per task. In addition, accuracy was measured by recording the errors made, comparing the provided barcodes with the barcodes recognised. These two metrics, time per task and errors in task completion, are generally accepted as metrics to evaluate the usability in HCI [58].

5. RESULTS

Table 11 presents the number of iterations (Epoch) while training the ANN model by allowing 0.001% error rate, the training time (seconds) and the RMSE values measured for the FFANN model for each finger (index, middle, ring, pinky and thumb).

Table 11: The RMSE value for ANN with different features

	Epoch	Time	IF	MF	RF	PF	TF	AVG
RMS	4864	24.47	7.59	3.27	2.91	0.07	6.44	4,05
WL	772	47.72	14.92	0.22	3.0	3.10	0.005	4,24
Conv.	4447	119.9	3.08	8.44	1.54	0.03	6.32	3,88
RMS+WL+Conv	330	27,07	3.90	5.49	4.77	0.09	0.40	2,93

The table reports on error rates when using the three individual features (as discussed in Sections 3.2), as well as a combination of the three features. The last column provides an average error rate, indicating that a combination of the three features provides the best results while classifying gestures in the gesture-group.

Table 12: Number of inputs assessment

	Total	Experienced
Expected Inputs	1560	390
Inaccurate Inputs	1053	112
Total Inputs	**2613**	**502**
Accuracy Rate	**59.7%**	**77.6%**

Table 13: Time assessment in second

Total Time	**7237**
Total Inputs	2613
Time Per Input	2.76

As shown in Table 4, of 2613 number of inputs provided by the eight participants, 1560 were accurately recognised and 1053 were inaccurately recognised. The table also shows an accuracy of

77.6% has been achieved on input entry by two experienced participants, whereas all eight participants decreased down to 59.7% accuracy. Table 5 confirms that the MCIp was able to provide one input in 2.76 seconds on average when the MLU provides it with 25 rows of data per second (SRate of 40 *Hz*).

MCI. We did not measure or take this into consideration while designing the experimentation.

Tan, et al. [59], as well as Mars and Abbey [60] suggested the short term meditation as a positively influencing factor which reduces the nonstationary state of bio-signals generated by the human brain. In this study it was found that the participants did not concentrate on performing a biological activity (moving muscles) on a purpose. A reason for the success of experienced participants was their prior knowledge of how the MCIp learns from them, and how it picks a specific behaviour out of their biological activities.

Table 14: The participants' performance while inserting 15 EAN-13 barcode numbers

	Average Time(s)	Inaccurate Input	Inaccuracy Rate	IF	MF	RF	PF	TF
P1	42128.8	50	25.64%	32%	30%	14%	12%	12%
P2	45009.8	62	31.79%	35.48%	37.1%	16.13%	6.45%	4.84%
P3	57168.2	112	57.43%	10.71%	28.57%	44.64%	12.5%	3.57%
P4	57953.46	123	63.07%	4.88%	7.32%	8.94%	33.33%	45.53%
P5	63149	141	72.3%	24.82%	34.75%	17.02%	14.18%	9.22%
P6	62055.73	144	73.84%	7.64%	5.56%	9.72%	45.83%	31.25%
P7	73070.26	200	102.56%	29.5%	46.5%	14%	3%	7%
P8	81947.26	221	113.33%	9.05%	31.22%	38.91%	7.24%	13.57%

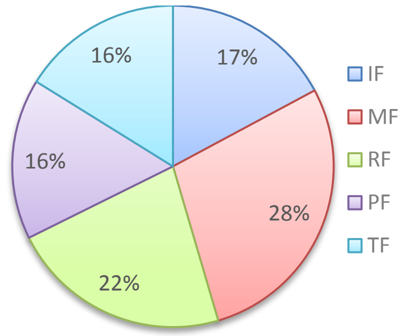


Figure 16: the gesture recognition inaccuracy based on each gesture

In Figure 16 it is seen that the highest inaccuracies (28%) with predictions were observed while classifying the middle finger (MF) where the thumb and pinky fingers were recognised as highly accurate (16% inaccuracies).

Figure 17 represents the inaccuracy rate based on box dimension and weight. It can be concluded that changes in the box had no specific impact on the trend of prediction accuracy.

Table 14 presents the information with regard to each individual participant and the metrics they are compared with, where participants are sorted by the degree of success per task. It must be noted that P1 and P2 are the two participants who had prior experience with the application of an MCI.

Table 14 highlights the two finger gestures the MCIp had the most difficulty in classifying, for each individual user. It is clear that these are always two adjacent fingers. The reason for this is the similarity of muscle group activities to form gesture for adjacent fingers.

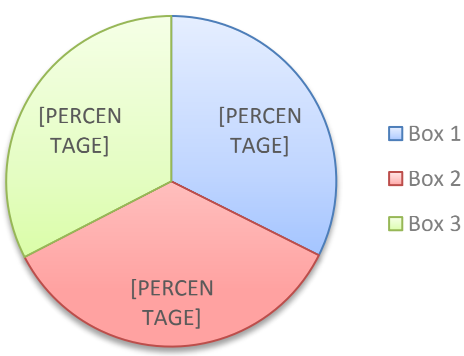


Figure 17: Number of inaccuarate input prediction per each box

6. CONCLUSION

The results presented in the previous section highlights some challenges regarding the use of the MCIp as a successful, accurate and fast HCI tool. It is noted that experienced users had a much better accuracy rate than novel users. Inaccuracy was observed less when the user had learned to interact with a system using an

The MCI is an economical potential technology that can open a variety of applications within the HCI. It can be improved in different fields since it is an emerging technology. The work reported in this paper has made a contribution towards MCI technologies, by introducing the use of feature extraction in order to improve gesture recognition when using the MYO armband. The MYO armband is currently the only user centred product in market supporting MCI. The paper suggests that the MYO armband has potential for input provision using MCI.

Future research is needed to improve the MCIp's accuracy. We suggest the degree of accuracy can be increased considerably by:

1- Changing the data collection for the calibration strategy;
2- Upgrading the ANN training method to allow the MCIp to learn more behaviours from the user continuously; and
3- Improving the ability of users in using their muscles for interaction.

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