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Contextual game design: from interface development to human activity recognition

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February 10, 2017

Resumo

O cancro de mama é considerado um problema de saúde pública pela Organização Mundial de Saúde, sendo também o tipo de cancro mais recorrente em mulheres, em todo o mundo.

Apesar dos avanços significativos em diversas modalidades de tratamento (*e.g.* Tratamento Conservador do Cancro da Mama, radioterapia, remoção dos nódulos linfáticos, ...), e da existência de programas de rastreio mamográfico, tratamento e acompanhamento no cancro da mama, as sobreviventes de cancro da mama estão ainda em risco de experienciar várias debilidades que afectam directamente o seu dia-a-dia. De entre os efeitos pós tratamento do cancro da mama mais comuns, é possível verificar uma maior prevalência da restrição de mobilidade do braço/ombro, assim como inchaço do braço, que deterioram a função corporal superior, que pode levar a linfedema crónico.

Considerando esta perspectiva, que tem sido identificada com bastante frequência, é imperativo que as mulheres mantenham uma actividade física específica e constante, de modo a obter mobilidade nos membros superiores do corpo considerada normal. Para isso, actividades a realizar em casa, de acordo com a avaliação clínica do estado da paciente, estão a ser apresentadas como a melhor opção de forma a garantir a melhor recuperação possível.

Atualmente, o emergente aparecimento de novas tecnologias levou a drásticas mudanças na sociedade. Um exemplo é a tecnologia associada a videojogos, que tem vindo a ser adaptada como parte de tratamentos médicos, com particular ênfase na fase de recuperação, quer para avaliação clínica como quer para maior motivação da paciente.

Neste trabalho pretende-se comparar um conjunto de interfaces contextualizadas com o problema de cancro de mama, que usam dados proveniente de um sensor Microsoft Kinect para monitorizar a paciente. Estas interfaces foram desenhadas com base nos fundamentos de jogos sérios, com o objetivo de exemplificar de forma interativa um conjunto de exercícios escolhidos pela comunidade médica. O funcionamento de cada interface proposta foi avaliada num setup clínico com um grupo de controlo composto por sobreviventes de cancro da mama. Por conseguinte, os resultados obtidos levaram a uma exploração do reconhecimento de atividade humana, de modo a melhorar a deteção de exercícios corretamente realizados pelo utilizador.

Em resumo, os objetivos deste trabalho são dar suporte e melhorar o período de reabilitação da paciente e avaliar as restrições funcionais causadas pelo tratamento do cancro, permitindo ao médico um seguimento do estado físico da paciente, com o intuito de melhorar significativamente a qualidade de vida da paciente.

Keywords: Cancro de mama; Tratamentos médicos; Função do Corpo Superior; Período de reabilitação; Jogos sérios; Sensor Microsoft Kinect.

Abstract

Breast cancer is not only considered a public health problem by the World Health Organization (WHO), but also reckoned as the most recurrent invasive cancer affecting women worldwide.

Despite significant advances on different treatment modalities (*e.g.* Breast Cancer Conservative Treatment (BCCT), radiation therapy, surgical removal of the lymphatic nodes, ...), and the existence of cancer treatment programs, breast cancer survivors are still at risk of experience several functional impairments with direct impact on theirs daily life. Among the most common breast cancer treatment-associated effects, it is possible to recognize a high prevalence of arm/shoulder restricted mobility and arm swelling, that deteriorate the Upper-Body Function (UBF) and may lead to chronic lymphedema.

Within such perspective, and as it has been recurrently identified, it is imperative for woman to sustain a constant and specific physical activity, in order to regain a normal UBF. For that, home-based programs, to be developed accordingly with the clinical assessment of the patient state, are being presented as a desirable path to follow for the best possible recovery.

Concurrently, a recent emergence of new technologies has led to major changes in society. For instance, technology from video games has being used as part of medical treatments, with emphasis in the recovery stage, to evaluate and motivate the patient.

The present work aims to compare a set of contextual interfaces, that uses data acquired with a Microsoft Kinect sensor to monitor the user. Furthermore, fundamental design guidelines from serious games are explored within the context of developing a system aid for physical follow up care in the form of a set of exercises selected by the medical community. The proposed interfaces were evaluate in a clinical set-up with a control group of breast cancer survivors. This assessment raised the need to tackle problems related with recognition of human activity. The later observation led to the study of human action recognition methods based on histograms of 3D joint locations in order to improve the interfaces detection of correctly exercises performed by the user.

In resume, the purpose of the subsequent work is to support and improve the patient rehabilitation period and assess the functional restrictions caused by cancer treatment, in order to evaluate the quality of procedures and to avoid further complications, while also allowing the clinician to follow-up the patient performance and ultimately improve significantly the patient Quality of Life (QOL).

Keywords: Breast Cancer; Medical treatments; Upper-Body Function; Rehabilitation period; Serious games; Microsoft Kinect sensor.

Acknowledgements

First of all, I would like to express my deepest gratitude to my advisor Hélder Oliveira, for giving me the chance to work in this engaging area. I sincerely appreciate his advice and guidance, his continuous support, his encouragement and his trust in me. I feel very lucky that he granted me the opportunity to join his group.

I would like to express my sincere thanks to João Monteiro for the time, the guidance, the brainstorming sessions and his encouragement. From whom I learned not only the foundation knowledge and state-of-the-art research, but also his dedication, patience and passion towards research. He gave me many helpful and insightful advice/contributions on my work.

To the Breast Research Group and INESC TEC a special thanks.

Also, I am very grateful to Dr. André Magalhães and Dr. Isabel Lopes of Hospital de S. João for the medical support in the data acquisition process.

A huge thank you to all the patients who put time and effort to test the interfaces created. Without them it would not have been possible to complete this work.

I feel lucky to have incredibly supportive friends. The courage and inspiration they gave enabled me to walk through all the difficulties.

To Francisco thank you for all the moments, distractions and encouragement.

Finally, I owe my thanks to my parents and my brother. Without their continuous support, encourage and love, this would not have been possible. I attribute all my success to them.

Carolina Lopes

*“ The road of excess leads to the palace of wisdom...
You never know what is enough until you know what is more than enough.”*

William Blake, Proverbs of Hell

To my Mother,

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Abbreviations

2-D	Two-dimensional
3-D	Three-dimensional
ALND	Axillary lymph node dissection
ANN	Artificial Neural Networks
API	Application programming interface
BCCT	Breast cancer conservative treatment
BCRL	Breast cancer-related lymphedema
CDT	Complete decongestive therapy
CGI	Computer-generated imagery
DCIS	Ductal carcinoma in situ
DBN	Dynamic Bayesian Networks
DNA	Deoxyribonucleic acid
fs	Sampling rate
FoV	Field of View
HCI	Human - computer interaction
HMM	Hidden Markov Model
HOJ3D	Histograms of 3D Joints
IDC	Invasive ductal carcinoma
ILC	Invasive lobular carcinoma
IR	Infra-red
k NN	k -Nearest Neighbors
M	Mean
ML	Machine learning
NUI	Natural user interface
NN	Nearest Neighbors
OMS	World Health Organization
P2P	Peer-to-peer
PPMP	Persistent post mastectomy pain
QOL	Quality-of-life
ROM	Range of motion
SD	Standart deviation
SDK	Software development kits
SLND	Sentinel lymph node dissection
SPQ	Self-Presence Questionnaire
SVM	Support Vector Machine
UBF	Sentinel lymph node dissection
UTD-MHAD	UTD Multimodal Human Dataset
VE	Virtual environment
VR	Virtual reality
WHO	World Health Organization

Chapter 1

Introduction

1.1 Context

Breast cancer is a matter of public health, with approximately 60% of incidence, being the one that affects females the most, having overall a tremendous impact on the woman body image and self-esteem given the aesthetic appearance of the breast [1]. Nearly 25% of the women diagnosed with breast cancer have malignant cells in the axillary lymph node system. Which implicates, besides the tumor removal, additional treatments have to be applied to remove the axillary lymph nodes [2]. Though, this type of procedures are usually accompanied with several upper-limb problems, comprising shoulder mobility, arm/shoulder pain and lymphedema. The former is a chronic disease that manifest itself with swelling of the hand, arm, chest, torso leading to a physical strain, and psychosocial functioning in patients [3].

Breast cancer survivors usually have to deal with long-term effects that will be a constant everyday which can also be accompanied with emotional distress, directly associated with the subsequent body changes results and its impairments [1]. Of all the complications of treating breast cancer, lymphedema of the upper limb is one of the most troubling and unpleasant for the patient, being also very frustrating to the surgeon [4]. The next five years after surgery are marked with arm/shoulder pain in the scale of 30-40%, of lymphedema 10-15% and conditioned arm/shoulder mobility is 15-30% [5]. These upper-body impairments are highly correlated with the QOL of breast cancer patient.

1.2 Motivation

An immediate study of the patient situation is imperative in order to put into action an appropriated and reliable rehabilitation program to prevent/attenuate these impairments in order to provide the patient a better QOL [6]. Therefore, it is the utmost necessity to detect as early as possible the development of side effects in order to identify which procedures have the best results to battle its adverse symptoms [7].

There are many ways to manage symptoms resulting of breast cancer such as exercises for Upper Limb Lymphedema (having in mind there are different levels of impairment), surgery, medication, manual lymph drainage, pneumatic compression, wearables for example. Although, most of this techniques have been shown as insufficient at some sort of level, the main reason being most of this procedures just treat the member in question without dealing with the movement of the confined lymphatic fluid long-term [8].

Resort to computational techniques such as Virtual Reality (VR) can be a source of motivation throw-out the recovery process of the patient. So the use of serious games in VR can became a great ally to the pre-existent procedures.

1.3 Objectives

In order to be possible to the patient regain full or at least a satisfactory level of mobility on the upper limbs, is imperative in the recovery stage a constant level of physical activity. So a list of exercises is prescribed, but sometimes the exercises are not done as they should and/or as frequent.

The main purpose of the following work is to solve this problem with a new rehabilitation tool. The basic premise is to show the patient how to do the exercises properly in the comfort of their own home, and at the same time, doing an evaluation of its overall performance concealed as a serious game using as resource some type of sensor.

The exercises will have been main focus in the affected upper body members in order to help regain as much as possible arm/shoulder mobility and prevent the risk of developing arm/shoulder impairments. The work aims to implement a series of interfaces for rehabilitation of breast cancer patients with partnership of researchers from S. João hospital, the data recover from its test subjects will be used to evaluate the research done.

In resume, this work focus on developing and testing of various interfaces, subsequently improve and test particular aspects such as, Microsoft Kinect joint location accuracy and action recognition.

1.4 Contributions

This work had the following main contributions:

1. Eight different interfaces were develop using the Microsoft sensor and Unity game engine, with six of them tested in breast cancer patients;
2. An already seizable database with collected data, was composed by diverse exercises and movements typically used for breast cancer patients, which can be further used in other works in the area like movement recognition, for example. This dataset composed by skeleton positions and color images is expected to continue growing for a year, approximately;
3. An application to simulate a goniometer was implemented, tested and validated;
4. A study and implementation of a simple framework for human action recognition.

1.5 Dissertation structure

After this section, this document is composed by seven more chapters. Chapter 2 presents a biological overview of the breast and breast cancer condition and in Chapter 3 a technological overview is done from subjective methods UBF assessment and human tracking systems are analysed. Also, some insights of RGB-D cameras are provided focusing in the Microsoft Kinect. Lastly, a analyses of several tools/programs to create a game environment and its components. In Chapter 4, a literature review of Human-Computer interaction and analysis of serious games in healthcare. Chapter 5, describes the application conception and results of the developed interfaces. In Chapter 6 which describes the implementation, methods and results for an application which simulates a goniometer. A study and a explanation of the framework created. And, in Chapter 7 shows the study and development of a framework for action recognition. Lastly, Chapter 8 is composed by a conclusion to the presented research and possible future work.

Chapter 2

Medical overview

2.1 Breast Anatomy and Physiology

The breast (see Figure 2.1) refers to the front of the chest or, more specifically, to the mammary gland responsible for producing milk being composed mostly of fat with a shape resembling a teardrop. Within this organ a complex network of branching ducts that exit from sac-like structures called lobules, which can produce milk in females. The ducts exit the breast at the nipple [9].

The lobules and ducts are supported in the breast by surrounding fatty tissue and ligaments. In the breast there are blood vessels and lymphatics, thin channels similar to blood vessels; they do not carry blood but collect and carry tissue fluid which ultimately reenters the blood stream. Breast tissue fluid drains through the lymphatics into the lymph nodes located in the underarm (axilla) and behind the breast bone (sternum) [10].

Although the primary biologic function of the breast is to produce milk to feed a baby, the breast has for many centuries been a symbol of femininity and beauty. The appearance of the normal female breast differs greatly between individuals and at different times during a woman's life before, during and after adolescence, during pregnancy and menstrual cycle, and after menopause [9].

The lymphatic system is part of the circulatory system and a vital part of the immune system, comprising a network of lymph nodes distributed along the lymphatic vessels that carry a clear fluid called lymph that contains tissue fluid and waste products, as well as immune system cells. Also, helps to maintain fluid balance in tissues and to absorb fat from the digestive tract. In the upper-limbs, all the lymph vessels drain into the lymph nodes in the axilla [12]. Furthermore, axillary nodes receive fluid from the upper back and shoulder, the lower neck, the chest, and the upper anterolateral abdominal wall. Approximately, 75% of the drainage of lymph fluid of the mammary gland is performed via lymphatic vessels into axillary nodes [13].

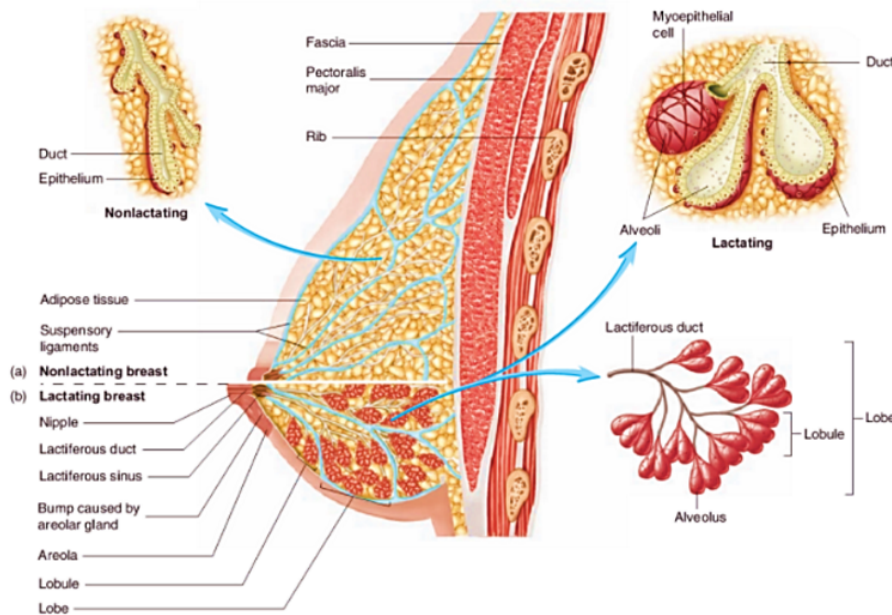


Figure 2.1: Breast Anatomy: (a) Nonlactating breast, only with the duct system (b) Lactating breast, with alveoli at the ends of the ducts, produce milk, (From [11])

2.2 Cancer

Cancer is defined by an abnormal and unregulated growth of cells, which may appear into surrounding tissues. It can occur in almost every part of the human body. Usually, human cells grow and divide to form new cells (replacing the dying ones) to match the needs of the human body, this cell cycle is regulated by Deoxyribonucleic acid (DNA) [12]. This regulation is done by two gene groups: oncogenes, responsible to promote cell growth and reproduction and suppressor genes, which constrains cell division and survival. However, this orderly process breaks down in the presence of cancer. The regulatory mechanisms become unable to prevent the perpetuation of this error, the cell starts to replicate without control, old and/or damaged cells survive when they should die, and new cells form when they are not needed, this may result in growths called tumors [14].

The regulation of those phases is mainly performed by two gene categories: oncogenes, which promote cell growth and reproduction, and tumour suppressor genes, which inhibits cell division and survival. If an over-expression of an oncogene or an under-expression of tumour suppressor genes occur, and the regulatory mechanisms do not prevent the perpetuation of this error, the cell starts to replicate without control [15].

Cancerous tumors are considered malignant, once they are able to spread into, or invade, nearby tissues. In addition, some cancer cells can break off and travel to distant places in the body through the blood or the lymph system and form new tumors far from the original tumor. On other hand, benign tumors do not spread into, or invade, nearby tissues. When removed, they usually do

not grow back, whereas malignant tumors sometimes reappear [14].

A malignant tumor forming from the cells of the breast is commonly known as breast cancer. These cells have a tightly regulated cell cycle that controls their growth, maturity, division and death. A cancer cell appears when a normal cell undergoes damage to the DNA that it is not repaired and the cell does not die, as it should. Instead, the cell undertakes division and the damage is propagated by the out-of-control growth of abnormal cells [13]. A malignant tumor forming from the cells of the breast is commonly known as breast cancer. The most common breast cancer frequently either develops in the cells of the lobules or the lactiferous ducts. The rarest, breast cancer takes its starting point in the stromal tissues, which include the fatty and fibrous connective tissues of the breast [16]. A study made in 2013, was found to be the most frequent in woman with 29% occurrence (see Figure 2.2) and the second deadliest with 14% [17].

2.2.1 Breast carcinoma

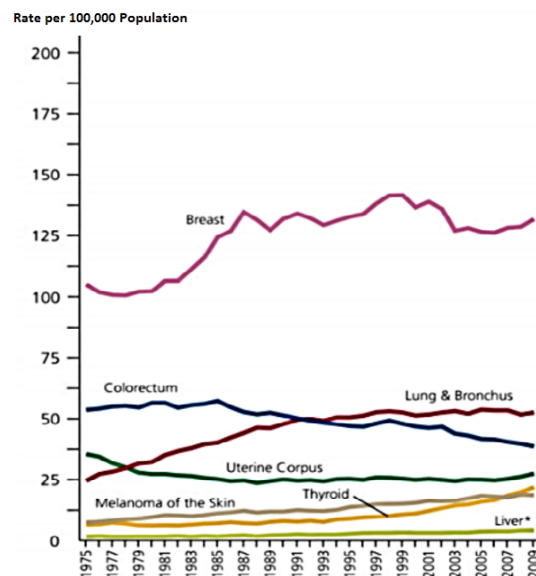


Figure 2.2: Incidence of cancers in women in the United States between 1975-2009, (From [13])

Breast cancer is frequently divided into non-invasive and invasive. Non-invasive breast cancer, also known as carcinoma in situ, is when the cancer remains within the place of origin and does not grow or spreads beyond the breast. Ductal carcinoma in situ (DCIS), one type of non-invasive cancer, is considered a pre-cancerous lesion. Which means that, although the abnormal cells have not spread out, they can eventually develop into invasive breast cancer. In invasive breast cancer, the abnormal cells spread outside the membrane that lines a duct or lobule, attacking the surrounding tissues. The spread of this cells can be made through the bloodstream or the lymphatic system to other parts of the body such as the bones, liver or lungs, creating metastasis. The most common types of invasive breast cancer are invasive ductal carcinoma (IDC) and invasive lobular carcinoma (ILC) (see Figure 2.3) [12].

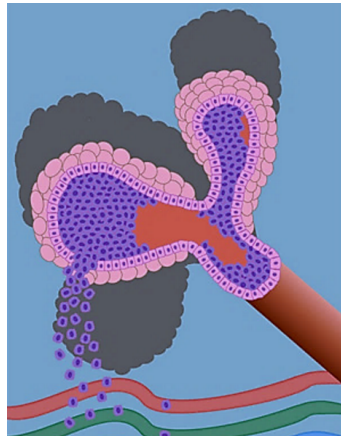


Figure 2.3: Invasive Lobular Carcinoma. The breast cancer cells originate in the breast lobules, (From [18])

2.2.2 Breast Cancer treatments

The clinicians approach to treat breast cancer as many factors to take in consideration, for instance women's general health and age, position and size of the cancer and how far it has spread. Also aims to reduce the risk of recurrence and/or its spreading (metastases), and obtain the best possible aesthetic outcome, relief of symptoms and restoring the QOL prior to diagnosis [18]. The treatments options normally include chemotherapy, radiotherapy and surgery. The treatment elected may be the surgical removal of the tumor by a mastectomy or a more conservative approach by Breast Cancer Conservative Treatment (BCCT) [19]. Non-surgical treatments, chemotherapy and radiotherapy, have an important role in order to prevent reemergence. It might be used before surgery to help shrink the tumor or after surgery [18].

Mastectomy is the surgical removal of the entire breast. These are the following types [20]:

- **Simple mastectomy procedure:** the entire breast tissue, the nipple, areola and, in certain cases, the sentinel lymph node (first node of axillary lymph node) are removed (see Figure 2.4(a));
- **Radical mastectomy procedure:** this method is performed only in severe cases as metastases in to the pectoralis muscles is the one that causes the more damage. Encompasses the removing of the entire breast, the axillary lymph nodes and pectoralis muscles;
- **Modified radical mastectomy procedure:** the entire breast tissue and all the axillary content is removed (see Figure 2.4(b));
- **Skinsparing mastectomy:** this type of surgery consists in removing breast tissue through an incision made around the areola. This type of procedure allows the reconstruction of the breast;
- **Nipplesparing/subcutaneous mastectomy:** breast tissue is removed but the nipple-areola complex is preserved. This procedure is recently used for tumors outside the subareolar position.

For most women in initial stages of breast cancer, BCCT is as effective as mastectomy since the survival rates of women treated with both approaches are similar [21]. This procedure preserves

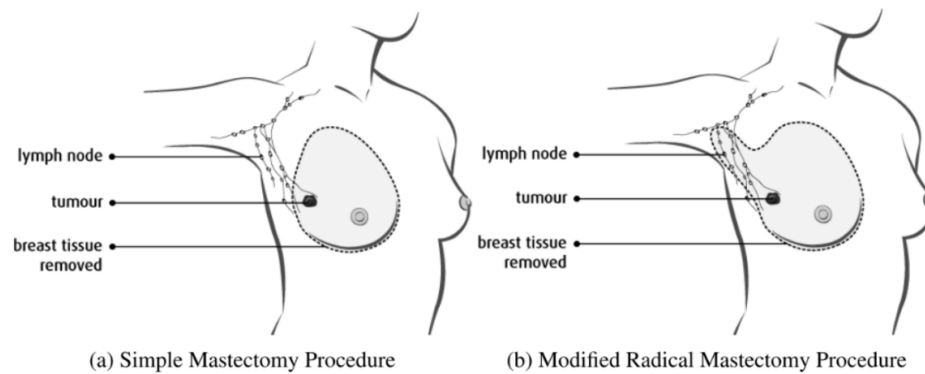


Figure 2.4: Common mastectomies procedures in breast cancer patients, (From [20])

the breast without compromising the survival of the patient. In breast conserving surgery it is only removed the tumor and some of the normal tissue that surrounds it, while preserving the natural shape and appearance of the breast. BCCT also includes a phase of radiation therapy after the surgical removal of the tumor in order to eradicate any residual cancer cells. However, side effects of radiation therapy, caused by interference on lymphatic drainage, include swelling and heaviness of the arm that will affect its mobility [22].

2.2.3 Lymph Node Dissection

The axillary lymph node status represents one of the most important prognostic factors in breast cancer patients and determines among others subsequent treatment. The percentage of node positive patients who benefit from routine axillary lymph node dissection (ALND) is constantly decreasing as breast cancer is increasingly detected at an early stage. About 40% of women diagnosed with breast cancer have cancer cells in their axillary lymph nodes [23]. As a result, in addition to the removal of breast cancer through one of the methods mention prior, often is necessary remove of one or more axillary lymph nodes to discover if the cancer has spread beyond the breast, so it is necessary to perform a lymph node biopsy to determine the following treatment [24] (Figure 2.5). The patients which will undergoing ALND there is a high probability of developing severe impairments in upper-extremity function since the removal of lymph nodes will affect the drainage of the limbs. So, significant impairments in UBF are associated with ALND, such as restricted arm and/or shoulder motion and arm edema [22].

An alternative to ALND is sentinel lymph node biopsy (SLNB), which can spare the patients a more invasive surgery and side effects, the procedure involves the identification and removal of sentinel lymph node, subsequently tested to determine whether cancer cells are present. Although, it has its own limitations and drawbacks. For context, sentinel lymph node (SLN) is defined as the first lymph node to which cancer cells are most likely to spread from a primary tumor. Sometimes, there can be more than one sentinel lymph node. In figure 2.6 – first panel, a radioactive substance

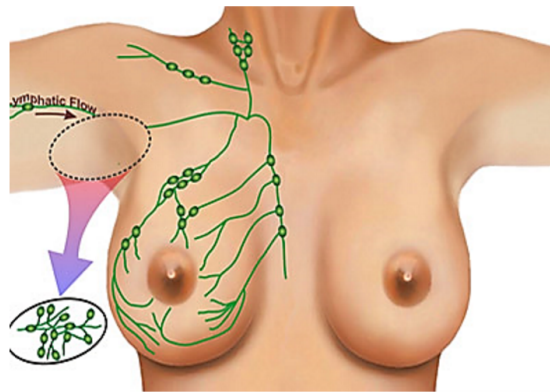


Figure 2.5: Axillary Lymph Node Dissection (ALND), (From [25])

and/or blue dye is injected near the tumor. In the second panel, the injected material is located visually and/or with a device that detects radioactivity. The last panel, sentinel node is removed and checked for carcinogenic cells [26].

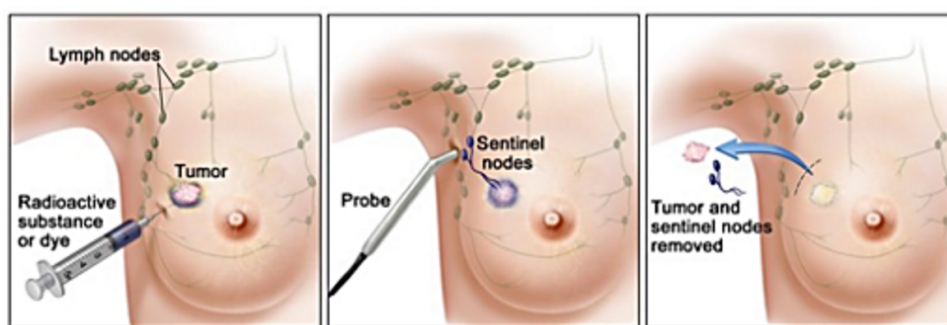


Figure 2.6: Sentinel lymph node biopsy of the breast, (From [25])

2.3 Impairments caused by breast cancer treatments

Persistent postsurgical pain is an increasingly documented problem, negatively impacting QOL and comprising approximately 20% of new chronic pain patients. The reported incidence of persistent post mastectomy pain (PPMP) ranges from 25-60%. In addition, developments in breast cancer detection and treatment have dramatically reduced mortality, around 2.5 million survivors in the United States. Among breast cancer patients, PPMP is rated as the most troubling symptom, leading to disability and psychological distress, and is notably resistant to management. While surgical factors, including more extensive surgery (total or partial mastectomy), axillary lymph node dissection and reconstruction have been suggested to serve as important risk factors for chronic pain, although several studies do not support this association [27]. Adjuvant treatment, such as radiation, chemotherapy, and hormone therapy, has also been associated with persistent

pain. Among demographic factors, younger age correlates with increased persistent pain incidence in some studies but not others. Preexisting pain is also more frequent in those who go on to develop PPMP [28].

2.3.1 Post Mastectomy Syndrome

The causes of post mastectomy pain syndrome are due to several factors although they remain uncertain. The most commonly cited theory is the removal of the intercostobrachial nerves that run through the axillary region into the arm which provokes chronic postoperative pain in breast cancer patients, estimated that up to 50% [29]. And in addition, chemotherapy and radiation therapy provoke neuropathies. This symptom provokes massive impairments in performing physical and recreational activities, increased body image distress, and decreased sexual interest and functioning. Injury to the nerves will result in neuromas due to ineffective regeneration and swelling within the nerves. Neuralgic quality pain (burning, shooting) associated with hypersensitivity, numbness, tingling, and muscle weakness depending on whether the nerve involved is purely sensory, purely motor, or mixed sensory and motor. The treatment involves physical therapy, topical agents, anti-convulsants, antidepressants, antiarrhythmic, nerve block and scar desensitization injections with dilute local anesthesia and steroids [29, 30].

2.3.2 Lymphedema

Lymphedema is a chronic disease which refers to swelling that generally occurs in one of your arms or legs sometimes either arms or legs swell. Lymphedema is most commonly caused by the removal of or damage to your lymph nodes as a part of cancer treatment. It results from a blockage in your lymphatic system (see Figure 2.7), which is part of your immune system. The blockage prevents lymph fluid from draining well, and the fluid buildup leads to swelling. However, it can be managed with early diagnosis and diligent care of your affected limb [31].

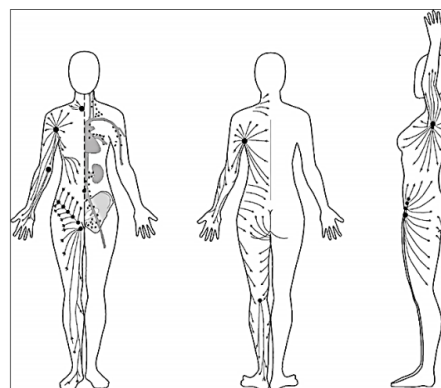


Figure 2.7: Normal lymph flow in skin, towards the lymph nodes, (From [32])

2.3.2.1 Lymphedema incidence in breast cancer patients

Patients undergoing axillary surgery and/or axillary radiation therapy for breast cancer are at higher risk for developing lymphedema of the arm, such treatments previous mention such as axillary node removal, sentinel node biopsy and local radiation [33]. Breast cancer-related lymphedema (BCRL) is a progressive, debilitating condition affecting millions of breast cancer survivors with a significant negative impact on QOL, employment and health, and it is not limited to arm swelling alone. Many survivors have complex symptoms which include breast and truncal swelling [34]. The amount of breast cancer-related arm edema can range from mild to severe, but once the condition starts, there is the possibility of progression to more severe lymphedema [31]. Even in early stage breast cancer, one study showed that when lymphedema progressed, lymphedema therapy could not completely reverse it.

2.3.2.2 Methods for Lymphedema Assessment

Lymphedema detection is normally assessed comparing the limb volume with the unaffected limb. The Table 2.1 shows the most common approaches, with a brief summary of each procedure in Table 2.2.

Table 2.1: Comparison of the most significant methods for Lymphedema assessment, (Adapted from [33])

Method	Time consumed	Applied at home	Accuracy	Cost	Complex
Water Displacement	Low	Yes	Low	Low	Medium
Circumferential Measurements	High	Yes	Low	Low	Low
Perometer ®	Medium	No	High	Medium	High
CT	Low	No	High	High	High
DEXA	Low	No	High	High	High
BIS	Medium	No	Medium	High	Medium

Table 2.2: Brief description for Lymphedema assessment methods, (Adapted from [33])

Method	Procedure summary
Water Displacement	In a container with water the limb is immersed into and the amount of the displaced water represents the volume of the limb.
Circumferential Measurements	The volume is estimated assuming cylindrical/conic volumes between several measures taken along the limb.
Perometer®	The device scans the limb with infra-red (IR) light and assess limb volume at small intervals.
CT	The device scans the limb with IR light and assess limb volume at small intervals.
DEXA	Uses a tissue-specific mode with attenuation of X-ray dependent on the thickness, density, and chemical structure of the tissue examined.
BIS	Measures volume of the limb by comparing impedance values of both arms (small current passes the body).

2.3.2.3 Lymphedema treatments

Lymphedema treatment focuses on reducing the swelling and managing the pain. For instance, some of the treatments are the following:

• **Physical exercises:** in which the movement of the affected limb may encourage lymph fluid drainage and help improve everyday tasks (see Figure 2.8 and Figure 2.9), the exercises should not be strenuous or tiresome but needs to focus on gentle contraction of the muscles in the affected limb [35].

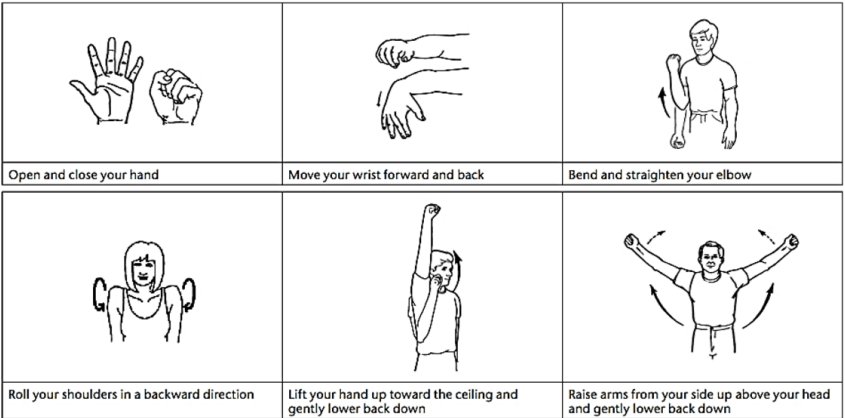


Figure 2.8: Specific Exercises for Upper Limb Lymphedema, (From [36])

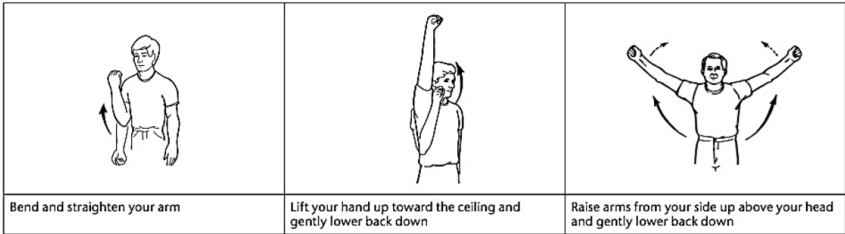


Figure 2.9: Exercises for Upper Limb Lymphedema where mobility is limited, (From [36])

• **Manual lymph drainage:** a specific massage technique called manual lymph drainage may encourage the flow of lymph fluid out of your arm or leg. This procedure is not recommending for every patient, should be avoid by whom displays symptoms such as skin infection, active cancer, blood clots or congestive heart failure. Also, the areas that were exposed to radiation therapy [37].

• **Pneumatic compression:** a sleeve worn over your affected arm or leg connects to a pump that intermittently inflates the sleeve, putting pressure on your limb and moving lymph fluid away from your fingers or toes (see Figure 2.10). Compression garments, long sleeves or stockings made to compress your arm or leg encourage the flow of the lymph fluid out of your affected limb [38].



Figure 2.10: Pneumatic compression pump, (From [36])

• **Complete decongestive therapy (CDT):** which involves combining therapies with lifestyle changes. Generally, CDT is not recommended for people who have high blood pressure, diabetes, paralysis, heart failure, blood clots or acute infections [39].

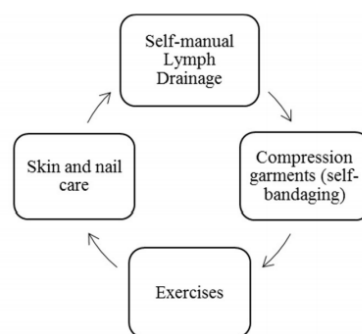


Figure 2.11: Phases of complete decongestive therapy, (Adapted from [40])

2.4 Summary

Nowadays, a more conservative approach in the treatment of breast cancer is a constant practice of the clinics. In the past years, the treatments haven't been suffering constant improvements, which contributed greatly for a less invasive approach. For instance, surgical procedures such as the radical mastectomy and ALND were replaced by BCCT and SLND, respectively. The last one manages to reduce the number of avoidable lymph node dissections. Even with these improvements which outcome is less extensive procedures, there is still a considerable level of morbidity in several patients [12]. The most recurrent impairment is in a restricted upper-body function, which includes reduced motion of the arm/shoulder, strength and flexibility, arm/shoulder pain and/or arm edema. That was caused by additional radiation therapy of the axilla or/and the lymph node removal. Both procedures interfere with the axillary lymphatic system [41]. Several methods of volume assessment of the upper limb are available, with water displacement as the gold

standard. In summation, restricted UBF as a direct correlation with the QOL of the patient, impact and sometimes dictate the lifestyle completely, having implications at a physical and emotional level such as chronic pain and depression [1].

Chapter 3

Technological overview

In this chapter, its done a technological review of state of the art available systems, assessment methods and accessible software's currently or possible applied in the rehabilitation of breast cancer patients. It begins with an overview of movement recognition systems, a key aspect to analyse change in the human body's pose, which requires a well-developed motion-sensor, leading to the followed section composed by an introduction of RGB-D cameras and an assessment of different sensors. Next the attention falls in several methods (subjective and objective) for UBF assessment. Lastly, it is contemplate some of the most relevant game engines available.

3.1 Movement recognition

The way humans interact with computers is constantly evolving, with the general purpose being to increase the efficiency and effectiveness by which interactive tasks are completed. Real-time, static and dynamic hand gesture recognition affords users the ability to interact with computers in more natural and intuitive ways [42]. Motion tracking (see Figure 3.1) is an essential building block of many advanced applications in diverse areas, for instance HCI (Human Computer Interaction) [43].

3.1.1 Non-visual tracking systems

Sensors available within these systems are placed in the human body with objective of collecting movement data. Being commonly classified as mechanical, inertial or microwave and magnetic based. In the general scheme of things, each type of sensor has its own advantages and limitations being particularly affected when exposed to different environments [44].

3.1.1.1 Magnetic sensor based systems

Magnetic motion tracking systems have various advantages, such as size, high sampling rate (fs) and shortage of blocking. Which make it largely used for tracking user movements in VR. However, also present some serious disadvantages, for instance latency (because of its asynchronous

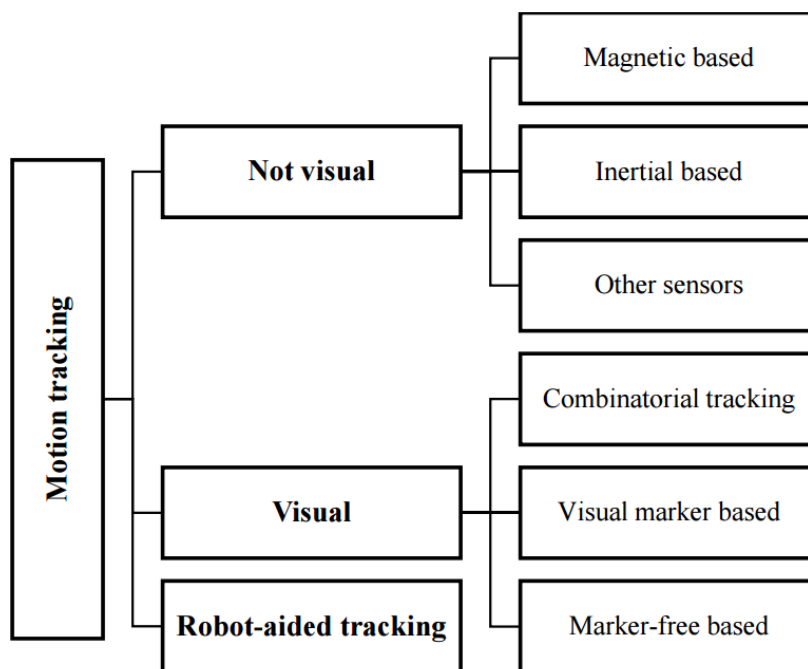


Figure 3.1: Classification of human motion tracking using sensor technologies, (Adapted from [44])

nature), jitter (appears in the existence of electronic or ferrous devices in the surroundings), and noise in the measurements. To tackle these problems, numerous research projects have been done, having its basis in predictive filtering methods [44].

3.1.1.2 Inertial sensor based systems

Inertial sensors are based on inertia, this sensors are easy to use and cost efficient way for full-body human motion detection. For instance, gyroscopes and accelerometers are often used in navigation and augmented reality modelling. The motion data can be transmitted wireless to a work base for further process or visualization. Inertial sensors can be of high sensitivity and large capture areas. For example, a project developed with this technology: Displacement Estimation in Micro-Sensor Motion Capture, with the following main objectives [45]:

- Multi-modal sensor data in order to attain high accuracy and low drift;
- Combination of the motion models to obtain full body motion model;
- Build a power effective and low error rate motion model.

3.1.2 Visual based tracking systems

Optical sensors (e.g. cameras) are routinely applied to improve precision in position assessment. Having as a precondition on whether the indicators need to be attached to body parts, tracking systems can be classied as either visual marker or marker-free [44].

3.1.2.1 Visual marker based tracking systems

Visual marker based tracking systems consists in using cameras to track human movements, with the visual markers positioned on the human body. Subsequently, an image processing program combines the 2D data and calculates the 3D position. The human skeleton is a vastly articulated structure and its different members have a random and intricate motion trajectory, which might cause an inconsistent and defective motion estimation. Other factors, may also introduce errors in the real position of the marker, such as mixt lighting or cluttered scenes [44].

Moving Light Display from *Johansson* in 1973, was the first work in this field, consisting in tracking trajectories due to reflective markers positioned in human joints. Nowadays, the purchase of these systems is a quite common thing and it is a growing sector. In controlled conditions this method is very accurate, being a reason to knowledgeable experienced investments from fields as animation movies and computer-generated imagery (CGI).

One example, is shown in Figure 3.2 which demonstrates a procedure for unconstrained wrist and elbow motions developed by *Schmidt et al.* [46]. However, the sensors need to performed some corrections in the results due to the influence of skin-movement on join angles. Besides, for patients with complications in upper limb it can become troublesome to setting the sensors the system requires, and a lot of calibration and professional intervention are needed.

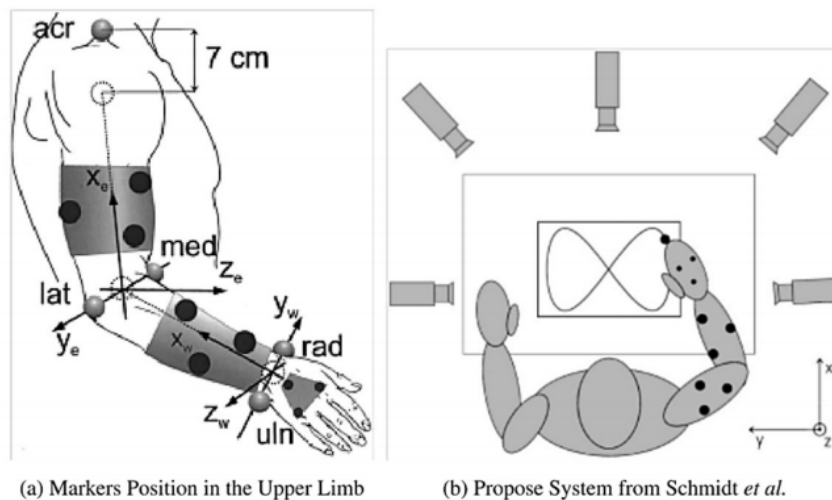


Figure 3.2: Markers and camera position in *Schmidt et al.* system. (a) Disposition of the markers (b) 5 cameras are used to pick the localization of the markers, (From [46])

3.1.2.2 Marker-free visual based tracking systems

2-D approaches

A 2-D approach is a framework frequently used. This approach produces object models (see Figure 3.3) with acquired image data from arbitrary human movements, it merely concerns human movement in an image plane; due to its dimensions adapts in a simple and quick way. However,

there are natural restrictions, due to their viewing angle. To improve a tracker in an unpredicted environment, 2-D motion tracking does not necessary needs an explicit shape model. Normally, this approach appears in rehabilitation environments [44].

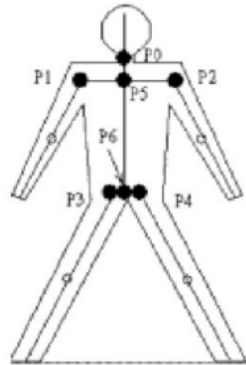


Figure 3.3: 2-D model of the human body, (From [47])

3-D approaches

3-D approaches for tracking human movements allows the tracking problem to be minimized. The future movements of a human body can be foreseen regardless of self-occlusion or self-collision. With these approach it is possible to constructed a 3-D model of an object by using various cameras(see Figure 3.4). This approach has been promoted as an alternative to 2-D modelling techniques [44].

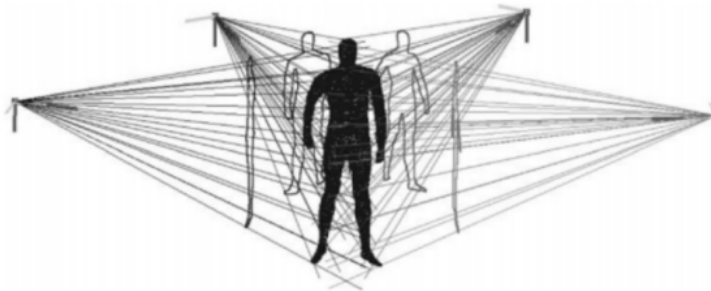


Figure 3.4: Concept of reconstruction of the shape of the object, (From [47])

3.1.3 Robot-aided tracking systems

Robot-aided tracking systems, is an established approach in rehabilitation systems that are driven by electromechanical or electromagnetic tracking approaches and, integrate individual sensor technologies to conduct "*sense-measure-feedback*" strategies. For instance, to delivering neuro-rehabilitation for human limbs following stroke [44].

3.1.4 Summary

People detection and tracking is an important and fundamental component for many robots, interactive systems and intelligent vehicles. Popular sensors for this task are cameras and range finders (see Table 3.1). Whereas both sensing modalities have advantages and drawbacks, their distinction may become obsolete with the availability of affordable and increasingly reliable RGB-D sensors that provide both image and range data [48].

Table 3.1: Performance assessment of different motion tracking systems according to Figure 3.1, (Adapted from [43])

Sensor	Accuracy	Compactness	Computation	Cost	Drawbacks
Inertial	High	High	Efficient	Low	Drifts
Magnetic	Medium	High	Efficient	Low	Ferromagnetic materials
Combinatorial	High	Low	Inefficient	High	Multidisciplinary
Marker	High	High	Inefficient	Medium	Occlusion
Marker-free	High	High	Inefficient	Low	Occlusion

3.2 RGB-D sensors

In recent years, a wide range of low-cost RGB-D sensors (see Table 3.2) have become available, consequence of a growth in the development of applications for home entertainment (*e.g* video games) using RGB-D sensors. Low-cost range sensors are an attractive alternative to other expensive scanners in application areas such as indoor mapping, surveillance, robotics and forensics. At the moment, acquire 3-D images using RGB-D cameras can be a quite simple task. This sensors capture RGB color images and depth data for each pixel. In order to produce depth estimates techniques as time-of-flight imaging and structured light stereo are commonly used. As an example, a frame obtain by using Microsoft Kinect sensor which provides dense depth estimates (see Figure 3.5) [49].



Figure 3.5: RGB image (left) and depth information capture (right) by an RGB-D camera. For the most part the white pixels in the right image means no depth value, due to occlusion, maximum distance, relative surface angle or material, (From [49])

Table 3.2: Available RGB-D sensors characteristics, (Adapted from [50])

Sensor	Type	Depth Range	3D Resolution	RGB Resolution	Frame Rate	Latency	FOV	Interface
ASUS® XtionPro™	Structured light	0.8 to 3.5 m	640 x 480	1280 x 1024	30 fps	1.5 frames	58° H, 45° V	USB 2.0
Live								
Microsoft® Kinect™	Structured light	0.5 to 8m	640 x 480	41280x102	30 fps	-	57° H, 43° V	USB 2.0
1.0								
Microsoft® Kinect™	Time of flight	0.5 to 4.5 m	512 x 424	1920 x 1080	30 fps	1 frame	70° H, 60° V	USB 2.0
2.0								
Intel RealSense R200	Stereo with pattern projector	0.6 – 3.5 m	640 x 480	1920 x 1080	60 fps (3D) 30 fps (RGB)	1 frame	59° H, 46° V	USB 3.0
Stereolabs® ZED™	Embedded stereo	1.5 to 20 m	2208 x 1242 max	2208 x 1242 max	15 fps at max	1 frame	96° H, 54° V	USB 3.0
Carnegie Robotics® MultiSense™ S7	Embedded stereo	0.4 m to infinity	2048 x 1088	2048 x 1088 max	15 fps at 2048 x 544	1 frame	80° H, 45° V	Ethernet

The analyse of RGB sensors focus on the Kinect sensor (which has gone through two versions), the reasons for this specificity are the following:

- The sensor is less expensive compare with the ones in the market [51];
- Numerous applications are develop in several sectors, with emphasis in the healthcare sector;
- There are a enormous amount of information compared to other sensors;
- It is integrated in numerous game engines (e.g. Unity, see Table 3.4).

3.2.1 Kinect v1 sensor

In November of 2010, Microsoft released a new Natural User Interface (NUI), the first version of the Kinect sensor (Kinect v1) as XBOX 360 gaming platform. Similarly, as other RGB-D sensors, the Kinect provides color information and the estimated depth for each pixel. The Kinect is an order of magnitude cheaper than similar sensors that had existed before it. This has dramatically strengthened interest in RGB-D sensors and their applications in areas such as NUI, reconstruction and virtual reality or 3D mapping [52]. The key hardware components of this sensor are illustrated in Figure 3.6 and a brief description is performed in Table 3.3.

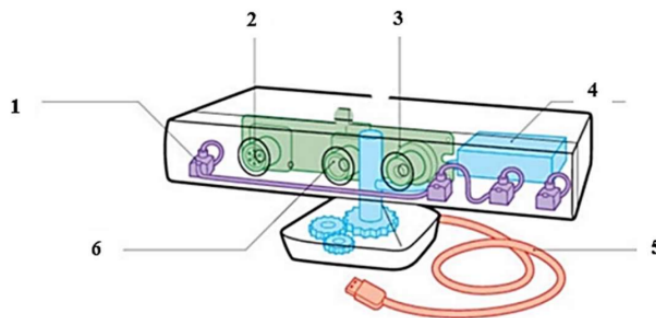


Figure 3.6: Kinect key components, (Adapted from [51])

Table 3.3: Description of Kinect central components, (Adapted from [51])

Components	Brief Description
1 Multi-array microphone	An array of four microphones able to separate the voices of the user from the background noise. The voice source can be placed as a result of comparing the delay in each microphone.
2 IR(Infra-Red) laser emitter	Dynamically emitting infrared spectrum, which are distorted by uneven surfaces and then randomly formed as reflected speckles that can be received by infrared camera.
3 IR camera	Capture infra-red signal which can potentially be converted into depth map.
4 Motorized tilt	The motor is programmed so it can achieve the best view angle.

3.2.1.1 Microsoft Kinect for Windows SDK

The Kinect for Windows SDK started by its very first beta version being a preview version with a temporary Application Programming Interface (API) and allowed users to work with depth and color data and also supported an advanced Skeletal. The first major update came along with the 1.5 version that included a Face Tracking library and Kinect Studio, a tool for recording and replaying sequences captured by the sensor. The Kinect for Windows SDK version 1.7 was released in March 2013 and included advanced libraries such as Kinect Fusion, a library for 3D scanning and reconstruction, and a library for hand grip detection which has opened doors for more natural way of interaction. The API of the Kinect for Windows SDK provides sensors depth, color and skeleton data in a form of data streams. Each of these streams can produce actual data frame by polling or by using an event that is raised every time a new frame is available [53]. The Kinect sensor, together with the Microsoft Kinect SDK provides the user with several streams of information such as:

- A stream of 2D color image frames;
- A stream of 3D depth image frames, the depth information is provided by the depth stream, which is represented as a frame of pixels that contains the distance in millimetres from the camera to the nearest objected. The depth data are represented as 16-bit unsigned integer value: the first 3 bits are reserved for the player segmentation data and the rest 13 bits for the distance, so the most distance stored in the depth data is about 8 meters. The depth frame is available in different resolutions (30 frames per seconds, for all), for instance its maximum resolution is 640x480 pixels [54];
- A stream of 3D skeletal frames, one of the most significant functionalities of the Kinect for Windows SDK is the Skeletal Tracking. In its field of view can identify up to 8 individuals and monitor for 2 users their actions. The skeleton which illustrates the skeleton space consists of 20 joints that represent the locations in X, Y, Z coordinates in meters of the key parts of the human body (see Figure 3.7). The tracking algorithm is designed to recognize users facing the sensor (the standing or sitting pose) with no particular pose or calibration action necessary for a user to be tracked [54].

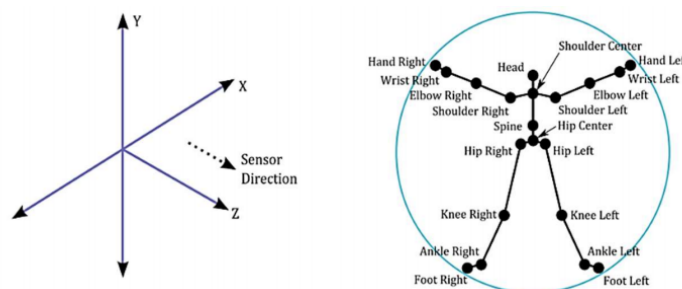


Figure 3.7: (a) An illustration of the skeleton space (b) Tracked skeleton joints overview, (From [54])

The process of developing a Kinect application was greatly expedited by availability of the skeletal joint 3D positions cause it freed developers from dealing with the complicated task of human pose estimation. Nonetheless, the accessibility to RGB and 3D depth frames enabled researchers and software developers to perform their own pose estimation instead of using the built-in skeletal frames provided by the SDK [55]. As an example, in a broad sense, the steps typically needed to develop a Kinect application involving human motion recognition are the following (see Figure 3.8):

• **Human skeleton estimation:** In order to achieve real-time human skeleton estimation, a model is developed to represent a human skeleton. Then, the model is trained with extensive labelled data. Finally, the trained model is incorporated in the SDK for real-time skeleton tracking. The main steps for human skeleton estimation include:

- Acquire the depth frames stream (needs to contain at least one human subject);
- Execute detection and foreground extraction of the subject (*i.e.*, background subtraction);
- To estimate the current pose, the extracted human subject is match with the trained model;
- Once the current pose is estimated infer the skeleton joint positions.

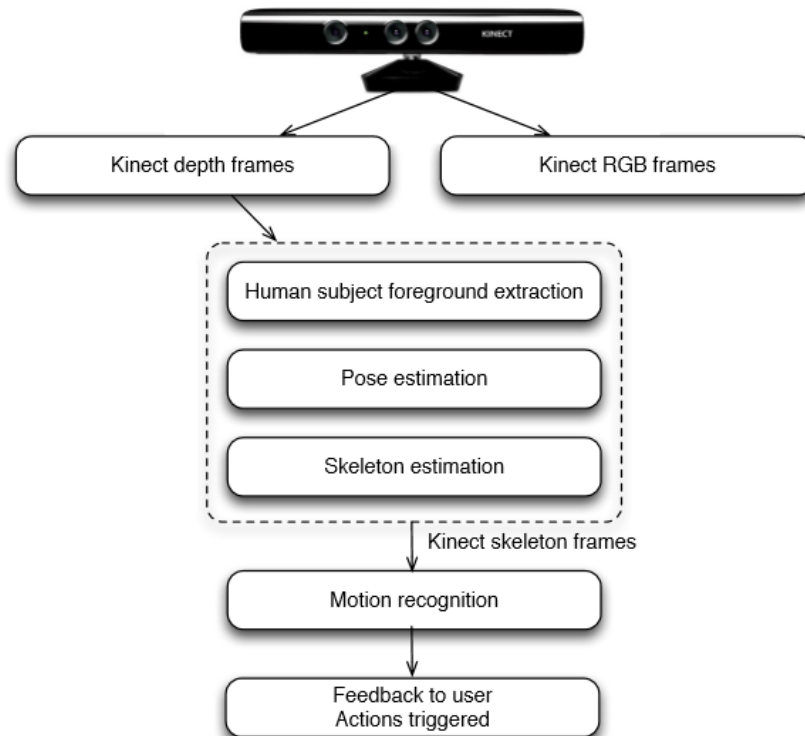


Figure 3.8: Typical steps of motion tracking and analysis with Kinect, (From [51])

- **Motion recognition:** For this part of the application, is recognised the gesture formed by the motion.
- Finally, feedback is provide to users and/or actions are triggered.

3.2.2 Kinect v2 sensor

The second version of Kinect (referred to as Kinect v2) was officially released in summer 2014. Kinect v2 (see Figure 3.9) uses a completely different depth sensing technology and offers much improved depth sensing accuracy as well as color image resolution. Compared with Kinect v1 it provides overall superior precision, responsiveness, and intuitive capabilities allowing a faster development of applications that respond to movement, gesture, and voice. The sensor's colour camera is enhanced with full 1080p video that can be displayed in the same resolution as the viewing screen [56]. The higher depth fidelity makes it significantly easier to image objects more clearly in three dimensions (3D).



Figure 3.9: External view of the Microsoft Kinect v2, (From [56])

The Kinect v2 has better overall performance, although its necessary a more recent software (see Table 3.4) and a Kinect v2 has a strong correlation of depth accuracy and temperature, resulting in the recommendation to turn on the device at least 25 min in order to achieve reliable results. The Kinect v1 captures reliable images already after a few initial images (see Figure 3.10). Another important disadvantages, it is the absence of a tilt motor in a running application. It is an important aspect in scenarios were testes are being perform in a sample population where the height vary from subject to subject.

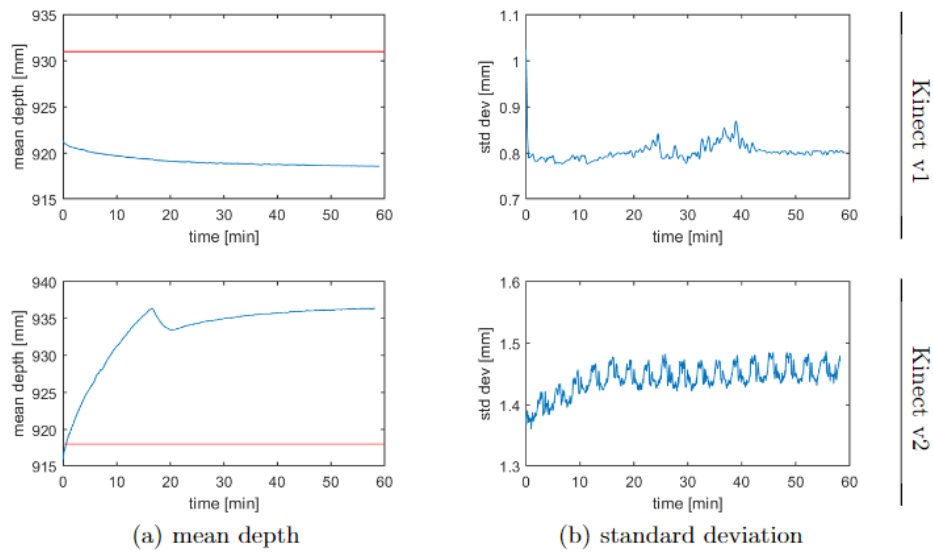


Figure 3.10: Evaluation of depth values over time, the sensor are pointed to a wall while the camera heats up. For the Kinect v1 the depth values slightly decrease but almost constant over time. For the Kinect v2 the depth values strongly correlate to the device temperature. The red line depicts the ground truth distance, (From [57])

Table 3.4: Comparison of main features of the two versions of the Kinect sensor, (Adapted from [55])

Feature	Kinect v1	Kinect v2
Depth Sensing Technology	Triangulation with structured light	Time of ight
Color Image Resolution	640x480 30fps	1920x1080 30fps
	1280x960 12fps	(12fps low light)
IR Image Resolution	640x480 30fps	512x424 30fps
	640x480 30fps	
Depth Sensing Resolution	320x240 30fps	512x424 30fps
	80x60 30fps	
Field of View	43° vertical	60° vertical
	57° horizontal	70° horizontal
Tilt motor	Yes	No
Skeleton Tracking	Up to 2 subjects	Up to 6 subjects
(with full skeleton)	20 joints per skeleton	25 joints per skeleton
Built-in Gestures	None	Hand state (open, close, lasso)
		Hand pointer controls; lean
Unity Support	Yes	Yes
Face APIs	Basic	Extended massively
Runtime Design	Can run multiple Kinect sensors per computer;	At most one Kinect per computer;
	One app per Kinect	Multiple apps share,same Kinect
Windows Store	Cannot publish to	Yes

3.3 Methods for UBF Evaluation

In this section, several methods for UBF evaluation are analysed. In Chapter 2, it was discussed the main causes and consequences of the breast cancer treatments regarding the UBF. It was stated the importance of a functional evaluation of the upper-body motion, in order to identify the procedures that present better results and to have a timely diagnosis in order to prevent further complications and, thereby, improve overall women's QOL. The approaches to evaluate UBF can be divided in subjective and objective. The most commonly used is the subjective method because of its low cost with encouraging results however [58].

3.3.1 Subjective methods for UBF assessment

Normally, UBF evaluation relies on subjective measurements of patients' experiences and function limitation. Thus, several generic self-report questionnaires have been developed to capture the effects of injury on the upper-body function (see Table 3.5) [59].

3.3.2 Objective methods for UBF assessment

Even though subjective methods have good results in UBF evaluation, it can be somewhat misleading. Thus, objective methods have been studied, including tests of flexibility, strength and endurance. The most common method is the goniometry, used to assess ROM in all planes [58]. After that, comparisons between limbs are performed, allowing the evaluation of abduction, flexion, extension, internal and external rotation. Endurance tests are usually performed using isometric and maximal performance of a set of tasks/exercises using the repetition maximum method, with each stage taking one minute and in each iteration exists an increment on speed of movement or weight held. However, objective methods are not usually used, since they have limited use to specify function, unlike subjective methods.

3.3.3 Key Timing of Measures

Measuring ROM function should be administered at key intervals along the cancer treatment and, the rehabilitation period that follows. The chosen time points should consider the natural course and expected rate of recovery from breast cancer, and the levels of change in the methods being applied (ROM assessment with goniometer, for instance). Measures should also be considered as a way to facilitate discussion among health care providers, employers, breast cancer survivors, third-party payers, and policy makers. Also, accurate documentation of symptoms and physical limitations may provide justification for funding and resource allocation at both a patient and program level [44].

Table 3.5: Main self-reports to UBF Evaluation, (Adapted from [60])

Self-report scale	Construct of Measure	Description	Clinical Interpretation	Validated in Breast Cancer Population
DASH	Pain related upper extremity disability	30 questions relating to symptoms (5 items) and functional tasks (25 items). Work and sports specific optional modules (4 items each)	0-100, a higher score reflects greater upper extremity disability	No
KAPS	Upper extremity problems (symptoms) and function	3 items consisting of 2 scales. Problem subscale (8 items) rating problems with upper extremity/shoulder function, pain, stiffness and swelling; ADL subscale (5 items) rating impairment of ADL	8-40, problem subscale; 5-25 ADL subscale. Higher scores reflect increased difficulty	Yes
ULDQ	Not Reported	80 items organized into 6 categories: symptom severity in the past 2 weeks; problem/symptom frequency in the past 2 week; current activity limitation; time relating to interference with normative work in the past 2 weeks; time with specified problems with work or daily activity performance in the past 2 weeks; and interference with weekly social, sports, or recreational activities in the last 2 weeks	Not Reported	Yes
Wingate	Functional status of women status postmastectomy over time	10 questions, each relating to degree of difficulty performing specified upper extremity tasks with the affected extremity	0-40, where lower scores are indicative of greater upper limb function	Yes

3.4 Game design

In order to design games several challenges are involved. In the vast majority of the cases it is require competences and understanding from diverse disciplines, including but not limited to game-play design, computer engineering, graphical design, interaction design, sound design, and script writing. [61].

3.4.1 Game engines overview

At this moment in time, there are several game engines featuring extensive documentation to ease the work in areas as coding, art and audio. In the following subsection, an overview of a select pair of game engines are done by their differentiating features from a general perspective [62]. Additionally, in order to develop a series of interfaces where the target public are breast cancer survivals, an analyse of specific parameters, such as asset pipelining capabilities, integration with NUI (Natural user interface) devices, physics engine support, 2D and 3D capabilities and flexibility.

Unity 3D is a commercial game development environment with a free version available. The main differentiating features are cross-platform capabilities and run-time compilation. Has a fully integrated development environment (IDE) allowing the whole game to be programmed, and to some extent its content as well (see Figure 3.11). Developers can alter the game directly via the GUI and see the changes instantly, while scripting via Javascript or C#. The cross-platform capabilities are quite significant, allowing deployment on most operating systems, mobile devices, browsers and even game consoles [62].



Figure 3.11: Unity3D screenshot: Interface development

- **Asset pipelining analysis:** As mention before, the asset pipelining is one of the strongest points of the Unity framework, given its integrated development environment. It also possesses the

ability to import files from the Autodesk .fbx file format, granting the ability to develop content in most 3D editors through their .fbx file exporters.

- **Integration with NUI devices:** It is theoretically easy to use the Microsoft Kinect SDK on the Mono framework, since the Kinect SDK is on the .NET framework and Mono is the cross platform implementation of the .NET framework.

- **Physics:** Unity3D already supports a physics engine, *NVidia PhysX*.

- **2D and 3D development:** Unity 3D is focused on 3D development, however, it allows the creation of 2D games by creating a flat 3D scene, which is meant to function in the same way as a normal 2D only game.

- **Flexibility:** Even though Unity 3D is cross-platform, it is not open-source. The addition of custom native libraries to be used within Unity is only possible with a paid license, which makes the incorporation of custom NUI input device libraries difficult.

Microsoft XNA is a Microsoft's Game Development Framework which is built on top of the .NET Framework and targets development for the PC, XBox360 and Windows Phone 7. The main differentiating point is the fact that XNA allows the development of games for a game console, something that usually comes with high licensing costs. XNA is also developed by Microsoft which means that it is ensured that it is very easy to incorporate components from the vast software areas encompassed by the .NET framework [62].

- **Asset pipelining analysis:** XNA has support for asset pipelining in the form of providing importers for a number of file formats such as models in Autodesk FBX files, X files (Microsoft's DirectX native files), and more, textures in most image file formats.

- **Integration with NUI devices:** Using the .NET framework brings possibly easier usage of the Microsoft's Kinect SDK since it is developed in the same framework.

- **Physics:** For 2D, the Farseer physics engine was created specifically for this framework. BulletSharp is a wrapper available for the 3D physics engine Bullet into XNA.

- **2D and 3D development:** XNA allows development of both 3D and 2D with equal focus on both.

- **Flexibility:** XNA is developed on top of the .NET framework which allows for compatibility with the vast resources provided in this framework however, it is ultimately not open source

3.5 Summary

Nowadays, it is very patent the evolution in tracking systems which has become a major application area in computer vision. It was addressed some of the current commercial technologies for human tracking based on markers placed upon the body and marker-free methods for motion tracking. Although, human tracking based on markers are efficient in this task, these systems are unreliable because of the use of markers whereas the equipment is very expensive and quite complex. Most of the existent marker-free methods for motion tracking have been at some extent effective in real situations. The drawbacks being related to robustness and efficiency that needs to be improved.

In summation, there is not a simple and worthwhile solution for assessment of upper-body movements that can be used in diverse environments, for instance a home setting base. As an alternative, RGB-D sensors can be a valuable approach to the traditional methods to track human movement. The years that follow the launch of the Microsoft Kinect sensor, in the end-consumer market a small revolution happened, for instance, research towards the use of a standardized consumer-grade RGB-D sensor for scene content retrieval [49]. For the purposes of this work, the Microsoft Kinect indicated worthy assets for the developer and the user.

As for the game design, the focus lies one existing game development frameworks were is discussed the value of an established content creation pipeline, following a summary and analysis of the desired framework's objectives in two existing game engines.

Chapter 4

Human-Computer Interaction

Until the late 1970s, the interaction between human and computer was very restrictive and seen as a niche with only information technology professionals and dedicated hobbyists. In the later 1970s, a disruptively change occur with the emergence of personal computing (includes personal software and personal computer platforms) which made everyone in the world a potential computer user. In the early 1980s, an area of research and practice emerged, Human-Computer Interaction (HCI), in the early stages as a field area in computer science taking on cognitive science and human factors. For the almost last four decades, HCI has expanded rapidly and steadily, appealing of professionals from many diverse areas such as, computer science, behavioral sciences, media studies, design and many other fields of study. Nowadays, to a considerable degree, HCI is now composed by an assembly of somewhat autonomous fields of research and practice in human-centered informatics. Nevertheless, HCI has produced an eye-open case of how poles apart areas can be reconciled and integrated in a productive logical project [63].

The means by which humans interact with computers continues to evolve rapidly, HCI is affected by the movements shaping the nature of future computing. These movements include [64]:

- Decreasing hardware costs leading to larger memories and quicker systems.
- Reduction of hardware and reduction in power leading to portability.
- Focused hardware prominent to new functions (e.g., rapid text search).
- Improvements in network communication and distributed computing.
- Increasingly widespread use of computers, particularly by people who are outside of fields generally related with use of computers.
- Increasing innovation in input techniques (e.g., voice, gesture), combined with lowering cost.
- Broader social awareness leading to improved access to computers by currently disadvantaged groups (e.g., young children, the physically/visually disabled).

4.1 Serious Games

As matter of fact, virtual and gaming environments applied to different areas, referred to as serious games (SG), present many new challenges to HCI [65].

A game, at heart, aims to offer the player a challenge of a physical or/and mental nature that can be completed using a set of rules, being able to install feelings of amusement or entertainment in the participant. Video games has the same goals, only a computer is used as an intermediary [66].

The oxymoron “*Serious Games*” is used to describe the development of games where the main focus is to achieve some change in the player. This idea of using games, more specific video games, to deal with serious matters is an incessant, moving and fairly new field. However, not being the main focus to create a game for amusing purposes, it somewhat defeats the purpose of the game if it is not a main factor to have in mind [67]. The game must have the ability to instill in the player a will to overcome the challenge that the game purposes.

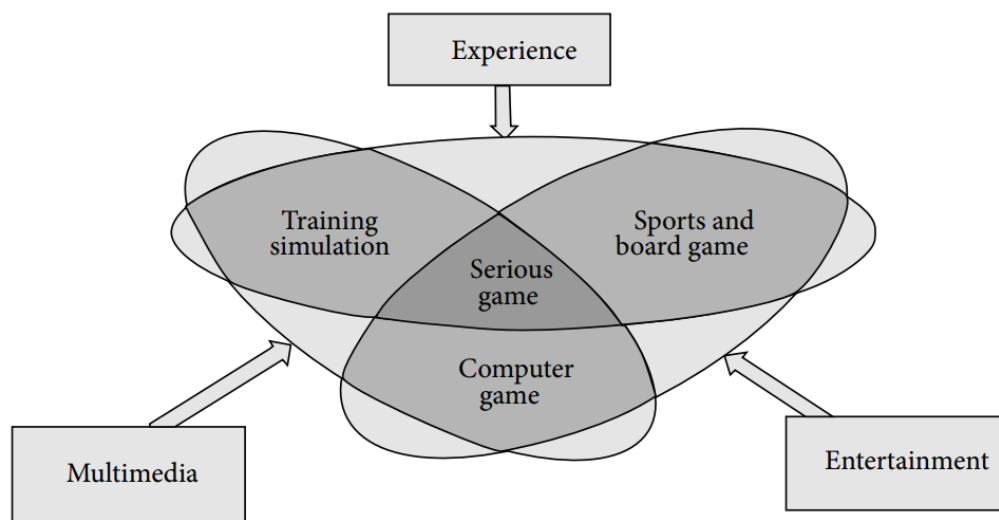


Figure 4.1: Definition of serious games, (From [66])

The number of serious games released on the market every year has been steadily growing, with the year 2002 (see Figure 4.2) instigating the starting point for the current trend. Several areas engage in developing serious games (see Figure 4.3) for instance, education monopolized the development of serious games before 2002; then, there was a uninterrupted growth of advertising area from 2002 to 2009 with 30.6%, in this period of time sectors such as health, government and policies also showed growth.

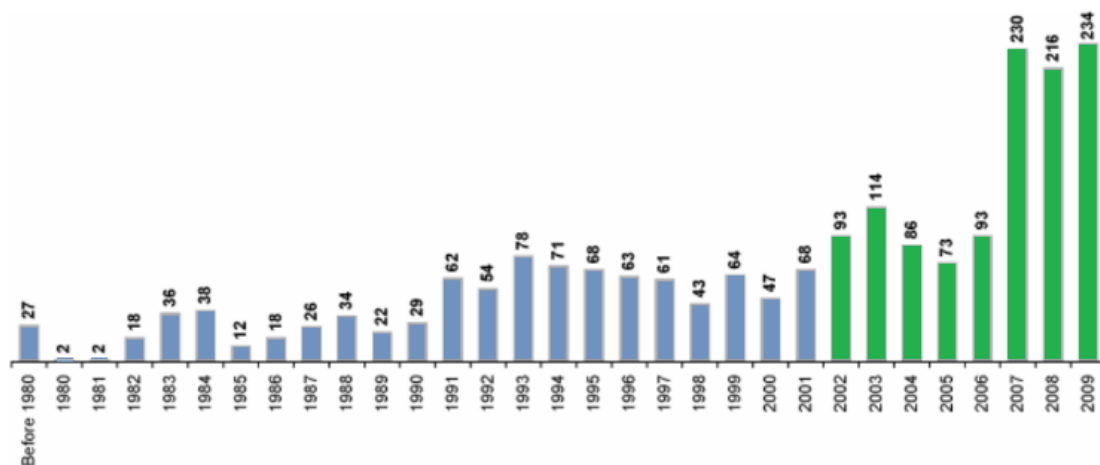


Figure 4.2: Number of “Serious Games” released each year up until 2009 [2218 games], (Adapted from [68])

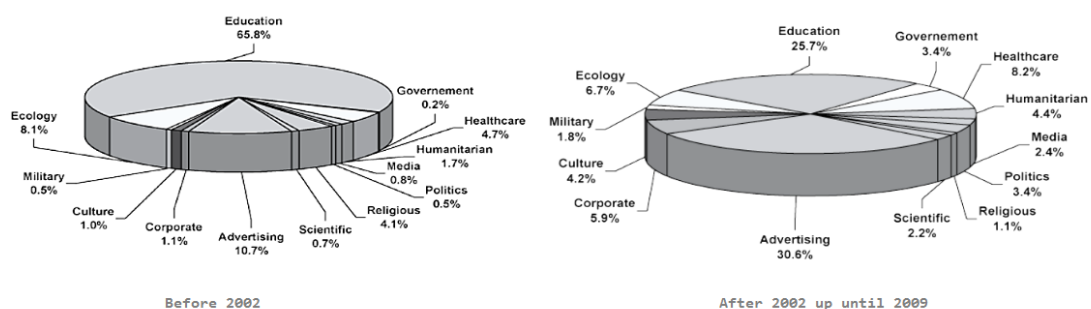


Figure 4.3: Market repartition of "Serious games" released before and after 2002 up until 2009, (Adapted from [68])

4.1.1 Serious Games for Rehabilitation

Analysing all the areas where serious games have had an impact, no doubt it's a term attributed to a lot of different aspects, that include video game design and development, hardware, software and game play. Just considering the area involving health and wellness space, a whole suite of serious games applications are being investigated in different capacities, such as: academia, government and by independent developers (see Table 4.1), reflecting an overall acceptance and awareness surrounding Serious Games opportunities.

Rehabilitation programs tested in patients with disabilities and impairments problems demonstrate that patients' function improves with an intensive training split, in particular tasks that are oriented in the achievement of a goal. However, this task division is a major fall-back, which is the lack of interest of the patient in performing repetitive tasks [69].

As traditional treatments approach include exercises often considered repetitive and boring for patients, a solution for this problem is in using computer games to augment physical and cognitive perception which can bring significant therapeutic benefits. Games require cognitive and motor activity in order to engage with the user. Most games offer levels with increase difficulty which helps the player adapting to the game also gives the player a sense of challenge. Another important aspect is that games serve as an escape from reality which can help in management of pain, for example.

The application of Virtual Reality (VR) technology for the rehabilitation of cognitive and motor deficits has been growing in the last decade and stroke patients have been one of the main target population for these new methods [70]. These VR based methods can offer the patients to be part of immersive experiences that are engaging and rewarding for them.

Table 4.1: The Games for Health Taxonomy developed by the Games for Health Project, (Adapted from [69])

Area of health activity	Personal	Professional practice	Research and academia	Public health
Preventative	“Exergaming” Stress	Patient Communication Pain distraction	Data collection	Public health Messages
Rehabilitation	Disease managment	Cyberpsychology Disease management	Virtual humans	First responders
Assessment	Self-ranking	Measurement	Inducement	Interface and visualization
Educational	First Aid Medical information	Skills and training	Recruitment	Management simulations
Informatics	Personal health records	Electronic medical records	Visualization	Epidemiology

4.1.2 Taxonomy for Rehabilitation Serious Games

A taxonomic approach means to assort issues by disciplinary topics allowing for discipline researches and, to integrate reasoning by lucidly relating issues of rather different disciplines. The main criteria for the classification of SG in rehabilitation falls in the following areas [71]:

- **Application area:** Where a game can be categorized in the following application domains:

- Cognitive rehabilitation (Cognitive), a process focus on the patients’s reacquisition of the most independent or highest level of function. Cognition is the mental action or process of acquiring knowledge and understanding through thought, experience and the senses.

- Motor/physical rehabilitation (Motor), include Parkinson’s disease, orthopaedic rehabilitation, functional activities of daily living training and stroke rehabilitation.

- **Interaction technology:** The technology used by the player in order to interact with the system. There are a spectrum of methods such as traditional methods (mouse or keyboard) to virtual reality (VR) based methods.

- **Game interface:** The interface used in the game which can be two-dimensional (2D) or three-dimensional (3D);

- **Number of players:** Number of patients playing the game: single-player (single) or multi-player (multi);

- **Game genre:** The game genre may vary according to the technology used. For example: games to evaluate movement (catch, reach and grasp) and games that are simulations, strategy, or combination of several (assorted);

- **Adaptability (Yes/No):** Capacity of the system to adapt the game difficulty dynamically, according to the patient performance in the game. If a player is not familiar with the game, at a start of a new game a low level is preferred in the beginning of the game. Some games, maybe do not have the identifiable levels, but indicate that the player has achieve an adequate level by a specific points, for example;

- **Performance feedback (Yes/No):** The ability of the system to transmit information while the player is playing; This feature can be used as a progress meter or used to identify correct or incorrect actions;

- **Progress monitoring:** System capacity to store data that can be assess later by the patient or clinic;

- **Game portability:** Relates to the ability of the system to be used at home or be contained within a clinical environment.

4.1.3 Examples of Rehabilitation Serious Games

Several serious games have been reported in literature some of them were already mention in Chapter 3, in this subsection is review some works that stand out in the rehabilitation area (see Table 4.2) with the criteria mention above.

Prior to this work, the research group VCMi from the INESC-TEC, has been working to build solutions for rehabilitation of patients with breast cancer. The most notable works are the following:

- Guerra [58], focus in the improvement of work done by Moreira [12], which consisted in developing an objective method to perform evaluation and provide a more accurate analysis of upper limb impairments. For that, a number of exercises were selected and, RGB-D and skeleton positions were acquired using data from Microsoft Kinect. It is not considered a serious game but served as baseline for the work by Costa [47].

- Costa, development of a rehabilitation model for patients who have had breast cancer through the use of Microsoft Kinect, the developed application allows the patient in executing useful exercises in order to recover the surgical operated limb. The rehabilitation model consists in two games which the objective is performing daily life tasks like iron the clothes, for example.

Table 4.2: Classification and Comparison of Serious Games for Rehabilitation, (Adapted from [71])

	Application Area	Interaction Technology	Game Interface	Number Players	Competitive/ Collaborative	Game Genre	Adaptability	Progress monitoring	Performance feedback	Portability
Barker et al. [72]	Motor	Body weight movement	2D	Single	None	Memory+ Simulation	Yes	Yes	Yes	Home
Ma et Bechkoun [73]	Motor	Motion tracking Speech + Touch +	3D	Single	None	Simulation	Yes	Yes	Yes	Clinic
Conconi et al. [74]	Cognitive	Motion tracking + Biosensors	3D	Single	None	Strategy	Yes	Yes	Yes	Clinic
Caglio et al. [75]	Cognitive	Keyboard	3D	Single	None	Simulation	No	No	-	Clinic
Cameirão et al. [76]	Motor and Cognitive	Motion tracking	3D	Single	None	-	Yes	Yes	Yes	Clinic/ Home
Ryan et al. [77]	Motor	WiiMote WiiBalance	2D	Single/ Multi	None	Maze	-	-	-	-
System RehaCom et al. [78]	Cognitive	Special keyboard + Joystick	2D	Single	None	Assorted	Yes	Yes	Yes	Clinic

4.2 Summary

As a field of research, HCI has experienced in the last decade a vast development leaving to a piecing together of many distinct areas such as computer science, behavioral sciences and media studies. Which results in improvements in various sectors of society, healthcare for instance. Nowadays, it is not new that humans and computers have a second hand connection with each other. And like everything that experiences such bound it is imperative to develop and take as much opportunity as possible.

Nowadays, digital games are introduced as something more than entertainment. Games that have a Serious purpose beyond entertainment, are called Serious Games. A serious game is defined as a context mental, played with a computer according to some rules which are used in different areas, such as: training, government, education, health, and communication.

There are a lot of examples that can be given to emphasis the impact that serious games have in improving healthcare in general. One of its examples, is *Captain Novolin* (Raya Systems, 1992) [79] designed to teach kids how to manage diabetes (released for the Super Nintendo console). Further studies showed that the game helped the children to learn how to manage insulin and to have healthy meals, in order to prevent glucose-related crises. However, when comparing SG to popular games generally, they lack qualities to be entertaining and motivating for patients. Also, most applications are prototypes and for a single-user player which are mostly used at clinics or hospitals.

In summation, our society is deeply engraved in a technological environment and it is imperative to use this stage to try to improve the QOL of people as much as possible, namely serious games in patients that are in a rehabilitation period.

Chapter 5

Interfaces for Breast Cancer Rehabilitation

As mention in Chapter 2, breast cancer treatment carries with it a high risk for side effects, that may negatively affect physical and psychological function. Treatments such as surgery, chemotherapy, radiation therapy and hormonal therapies cast both immediate and former side effects, generally associated with diminished function in the upper-body limbs. The most common side effects include: pain, lymphedema, fatigue and upper quadrant impairments, such as decreased shoulder ROM and strength, and reduced muscle length, which are susceptible to rehabilitation interventions [80]. Rehabilitation interventions for many of the mentioned common breast cancer-related impairments have additional efficacy in an early detection and treatment. Further, there is a strong evidence that indicate rehabilitation plays an integral role across the lifespan of the cancer survivor. It was acknowledge in Chapter 4, the lack of home based systems available for consumption that are reliable, easy to set/use and affordable at the same time which could be use by breast cancer survivors during the rehabilitation period.

Nowadays, most researchers in HCI are interested in developing new design methodologies, experimenting with new hardware devices, prototyping new software systems, and exploring new interaction paradigms. Substantial attention is given to the development of tools for the rehabilitation of patients suffering from some kind of disability is growing [81]. Where the use of serious games as part of these rehabilitation tools is becoming an habit.

Taking into account all that was mentioned above, the main objective of this work is to implement a system that is low-cost and easy to use from the user perspective, in places like clinical environment or home based. To archive this goal, a series of interfaces were implemented with certain variations in order to assess the preferences of the study population. This evaluation occur in sessions done with breast cancer survivals in a clinical environment, where the interfaces were tested and a questionnaire was filled out. Thus, the purpose of this chapter is to describe the methodology used, discuss the results and further work done accordingly with the information gather from the questionnaire.

5.1 Methodology

A technological selection was made taking into account a number of requirements, and a group of exercises was selected with the help of Hospital S. João medical staff, only then the interfaces were designed and developed. In order to test and evaluate the implemented interfaces, protocols were defined, questionnaires were analysed and the space where the acquisitions were performed was taken in consideration.

5.1.1 Technology Selection

In Chapter 3, was done an overview of the available systems, assessment methods and accessible software. In the field of marker-free visual based tracking systems, RGBD sensors is referred as an alternative for a more affordable hardware. Namely, Microsoft Kinect v1 sensor is one of the most low-cost and reliable for acquisition of full-body 3D data, also the most adequate one for medical acquisitions, due to its low cost and technical properties such as range and resolution of field of view. Furthermore, Microsoft Software Development Kit (SDK) allows an automatic body calibration, which is an important feature for more efficient acquisitions. The Microsoft SDK provides the tools and APIs, both native and managed, to develop Kinect-enabled applications for Microsoft Windows.

Moreover, Microsoft SDK allows the development of applications in the field of markerless motion tracking system due to its skeleton tracking algorithm that, using depth data, can determine the position of several joints on a human form [54]. The system has the possibility of detecting up to a total of 20 joints, each defined with coordinates (x,y,z) expressed in skeleton space. Some examples of the types of Windows applications that are supported in SDK [51] are the following:

- Recognize and track moving people with **skeletal tracking**;
- Determine the distance between an object and the sensor camera with **depth data**;
- Enable voice-activated applications by programming a grammar for use with a **speech recognition engine**.

In other hand, game developers have been using commercial game engines to create serious games, game engines such as the “Unity 4” by Unity Technologies (2014), or “Unreal Engine” by Epic Games, Inc. (2014) provide game developers with efficient tools to rapidly implement and test new ideas [82]. Developing state-of-the-art games requires both programming as well as design skills and, accordingly, these tools need to be easy to use for both programmers as well as designers.

Ultimately, the game engine selected was Unity version 4.6.0 to develop the interfaces. In Table 5.1, it is shown a brief resume of this game engine (a more complete study is done in Chapter 3), however two major factors contributed to this choice:

- Incorporate and control avatars in the game engine;
- Integration with NUI devices, more specific Microsoft Kinect v1 without the need of further 3rd party plugins.

Table 5.1: Properties of the chosen game engine, (Adapted from [62])

Engine	Asset Pipelining	Programming language	Scripting	2D/ 3D oriented	Target platform
Unity	Very good through IDE.	C C++ C#	Mono, UnityScript, C#, Boo, HLSL	Yes	Windows, OS X, Linux Xbox 360, Microsoft Windows Kinect, Xbox One, Wii U, PlayStation 4, iOS, Android, Unity Web Player, Windows Store

Computer animation in the past decade has become one of the most noticeable features of technology-based learning environments. By its definition, it refers to the process of generating an animated sequence using several still images or snapshots of images [83].

Autodesk Character Generator was used to create, customize, and download rigged (input virtual skeleton) 3D characters from a catalog which include different body types, outfits, hairstyles, and physical attributes.

From the 3D computer graphics software available, Autodesk Maya (see Figure 5.1) was select to animate the avatar that displays the sequence of the selected exercises. Then exported as a *.fbx* file, in order to incorporate in the game engine. Maya is an application that runs on Windows, OS X and Linux, used to generate 3D assets for use in film, television, game development and architecture. For 3D animations, objects (models) are built on the computer monitor and 3D figures are rigged with a virtual skeleton. For 2D figure animations, separate objects (illustrations) and separate transparent layers are used with or without a virtual skeleton [84].

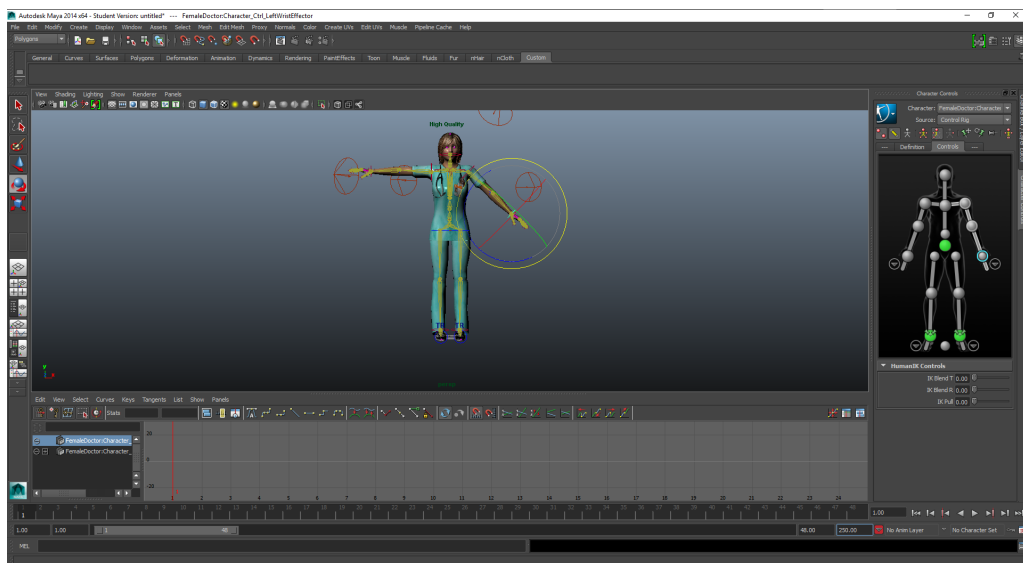


Figure 5.1: Autodesk Maya screenshot: Avatar exercise implementation

In short, the technological selection focused on selecting a RGBD sensor to acquire data which can be used for further evaluation and, to control the avatar assigned to the user by its skeletal tracking. Then, select the software for interface development, for the game engine the main requirement was its integration with the sensor.

5.1.2 Exercise Selection

One of the first steps was to select specific exercises to be performed by the patients in medical environment. To archive this goal some constraints were elaborated which were defined with the avail of medical staff, due to their knowledge in the area. Thus, the exercises performed must abide by the following requirements:

- Approved by the medical community;
- Intuitive, carrying into action by different people with various qualifications and ages without a problem;
- Pertinent, allowing the retrieval of information for future assessment;
- Adaptive, permitting its functioning in several conditions and places;
- Autonomous, meaning that the exercises can be performed without any extra material;
- Fully captured by the device during execution;
- Low time consuming.

Rehabilitation exercises are generally used in the recuperation of UBF, leading to tendon flexibility and enhancing muscular performance. One consequential factor is the phase of recuperation of the patient and the problems associated with surgery. Generally, the 1st step is to regain normal function of the patients upper limbs, generally advised to start by performing simple exercises such as daily routines (washing themselves, brushing their teeth) as soon as drains and sutures are removed [58].

The next stage, generally after the 3rd week of the post-operation period a regular exercise plan should be followed, with emphasis on stretching or reaching movements with exercises gradually becoming more complex and challenging. Small exercises are very difficult to capture with Microsoft Kinect because the movements performed usually have low amplitude of movement, the signal captured by the device can be very noisy. However, this is not a factor for exercises performed after the 3rd week given its broad range amplitude of movement. The exercises selected for this work were the following:

Exercise 1 - Arm out of Side: The patient starts with both arms in natural position then rises an arm and tries to cross it above the head from the side (see Figure 5.2(a)).

Exercise 2 - Range of Motion: The patient rises both arms laterally, trying to reach the highest height possible with the limbs (see Figure 5.2(b)).

Exercise 3 - Stick: The patient rises both arms frontally, trying to reach the highest height possible with the limbs (see Figure 5.2(c)).

Exercise 4 - Walk in Walls: The patient approaches a wall and, with the arm closer to it, tries to reach the maximum height possible, keeping the hand close to the wall during the exercise execution (see Figure 5.2(d)).

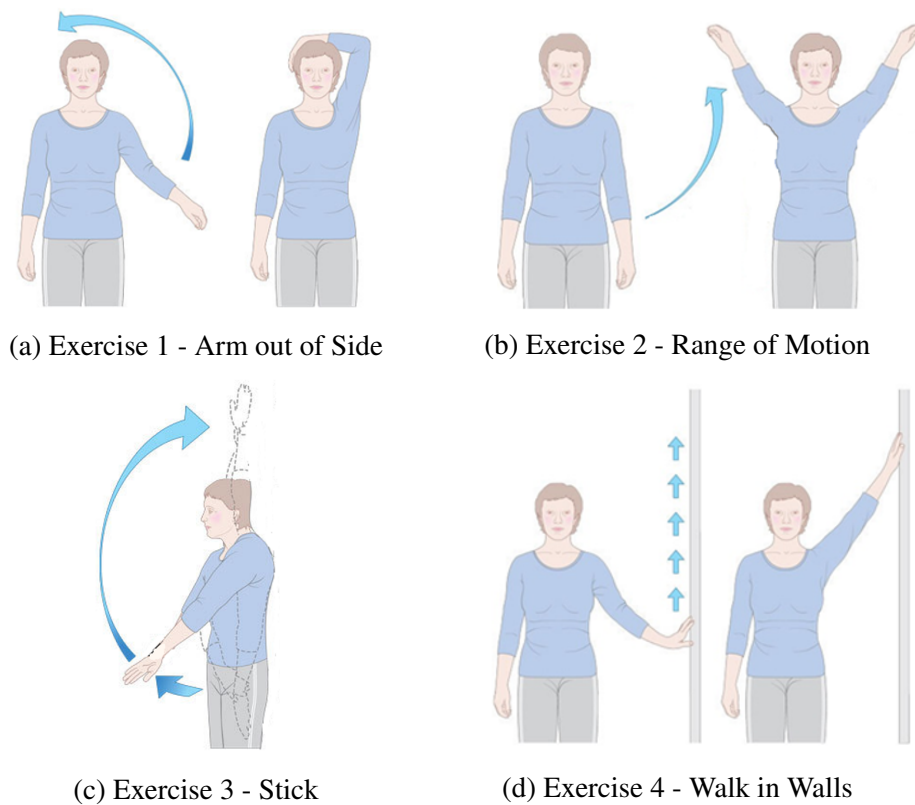


Figure 5.2: Exercises selection, (From [85])

5.1.3 Interfaces for medical data acquisition

As mention before, the main goal of his work is to design, develop and testing a series of interfaces. Once the study objectives were clearly defined and the boundaries of the domain delineated, specific variations between interfaces were selected for further assessment. Furthermore, a base-line for all the interfaces were thought off, taking in consideration the requirements of the medical staff that ultimately will operate the system, and the study population. It did result in a list of requirements (see Table 5.2) which focus on interface aspects and software requirements.

A brief explanation of these requirements is given below:

- **Status report in real time:** It is important to understand if the acquisition is going on properly, thus it is necessary to know the status of the sensor and if the skeleton position are being properly detected.
- **Intuitive display of the constitution/behaviour of the interfaces:** The interfaces must be intuitive, with a flow that is both easy to understand and predictable.
- **Exercises demonstration with an Avatar:** One objective of this work is to have in all of the interfaces, an avatar which will perform the selected exercises when an input in the keyboard is performed.
- **Possibility of repeating session, to rectify any error:** Due to possible errors in acquisitions, it is important to have a safety mechanism that lets patients repeat the session.

• **Data saving with the lowest user interference:** Since the user of the application might have little knowledge in technology, data saving must be automatic.

• **Low computational weight:** Due to the high amount of data to be saved, the application must be efficient in the saving process.

• **Prevent data losses:** Another important aspect is to prevent data losses, since relevant information can be lost in these. With this intent, a buffer was created and, when data cannot be saved, it is kept in this buffer until such saving can be performed.

Table 5.2: Main requirements for the interfaces

Graphic Interface	Visualization of the skeleton positions detected
	Display the status of Kinect
	Exercises demonstration with an Avatar
	Display the scores at end of simulation
	Intuitive display of the constitution/behaviour of the interfaces
	Instructions for using the interface available
Software Requirements	Possibility of various acquisitions (without having to close the interface)
	Possibility of repeating the session, to rectify any error
	Data saving with the lowest user interference
	Low computational weight
	Prevent data losses
	Motorized tilt kinect

Once, a set of requirements were established for all the interfaces, a total of four interfaces were developed and tested by breast cancer survivors. The interfaces are for one player only (see Figure 5.3), with the relevant information displayed for the player in portuguese.

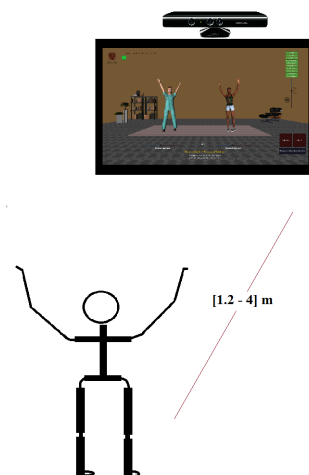


Figure 5.3: Interfaces usage scheme for single-player

Before starting to delve into the aspects of the develop interfaces, a nomenclature has to be used in order to facilitate its understanding (see Table 5.3).

Table 5.3: Nomenclature used to explain the development of interfaces

Termination	Meaning
Common components	Means the components or aspects that all the interfaces have implemented.
Medic-avatar	Corresponds to the avatar that demonstrates the exercises to be performed.
Player-avatar	Corresponds to the avatar assign and controlled by the player.

Considering the interfaces have a set of common components given the baseline that was sought at the beginning of this study, the exposure of the interfaces will begin with a set of common characteristics. Then, each interface will be individually described where the emphasis fall in aspects that vary from interface to interface.

5.1.3.1 Interfaces common components

All the developed interfaces have the same workflow, all start with a **Main menu** (see Figure 5.4) and has the following components:

Start the game: A input field is required to fill out with the user name or code before starting the game, to safeguarding that the acquired data can be identified.

Instructions (see Figure 5.5): An option to read on how to set and use the interface. To return to the main menu is done by pressing <Go back>.

Exit the game: The last option is to exit the interface by pressing the <Quit> button.



Figure 5.4: Interface components: Main menu

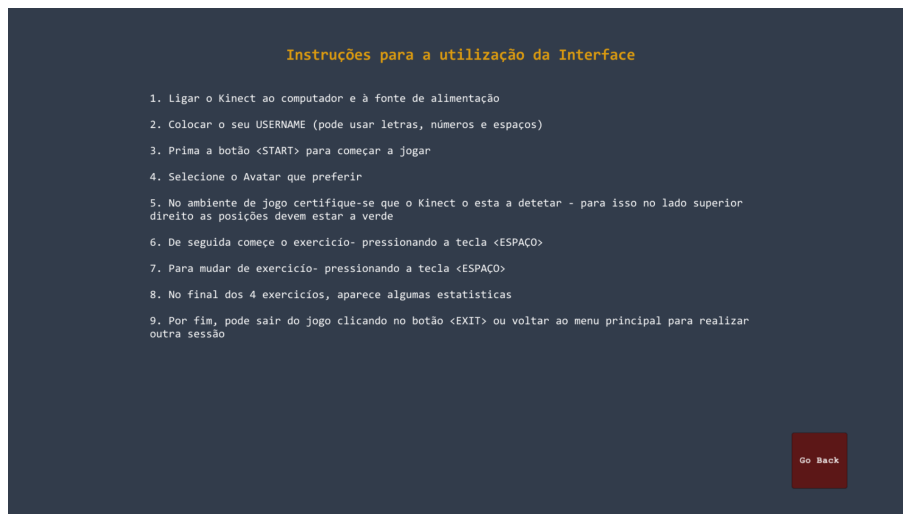


Figure 5.5: Interface components: Instructions

In the actual game environment, the common components are the following (see Figure 5.6):

- Data acquired using Microsoft Kinect is only being collect when the medic-avatar is performing an exercise and, when finished it is saved in different files (see Appendix B);
- Display of the status of the sensor, including a message of warning in case the sensor is not connected;
- Option in visualize a video with instruction on how to play, by click in the button <Demonstration video>;
- Option to tilt the Kinect sensor by input a value between -27° and 27° , to ensure that the user range of motion is capture;
- Information of what joints are being detected, in this case the joints of the upper-body are considered, in order to avoiding redundant elements which improves the overall appearance (a important aspect in game design);
- Adjusting the zoom of the application by the slider named "*Field of view*";
- Option to rotate the avatars with the slider named "*Rotate the avatar*", in order to improve the angle of vision to better perform the exercises;
- Every time an exercise begins, it is displayed the time spent in each exercise and the name of the current exercise;
- Between each exercise, a projection of the user is shown in order to adjust its position;
- The medic-avatar (see Figure 5.7) is animated with the selected exercises. When the game starts, the medic-avatar is still, to starting perform the exercise the <space> key needs to be pressed and to stop the exercise the <space> key needs to be pressed once again, and so on. When all the exercises are shown, a panel with statistics appears;

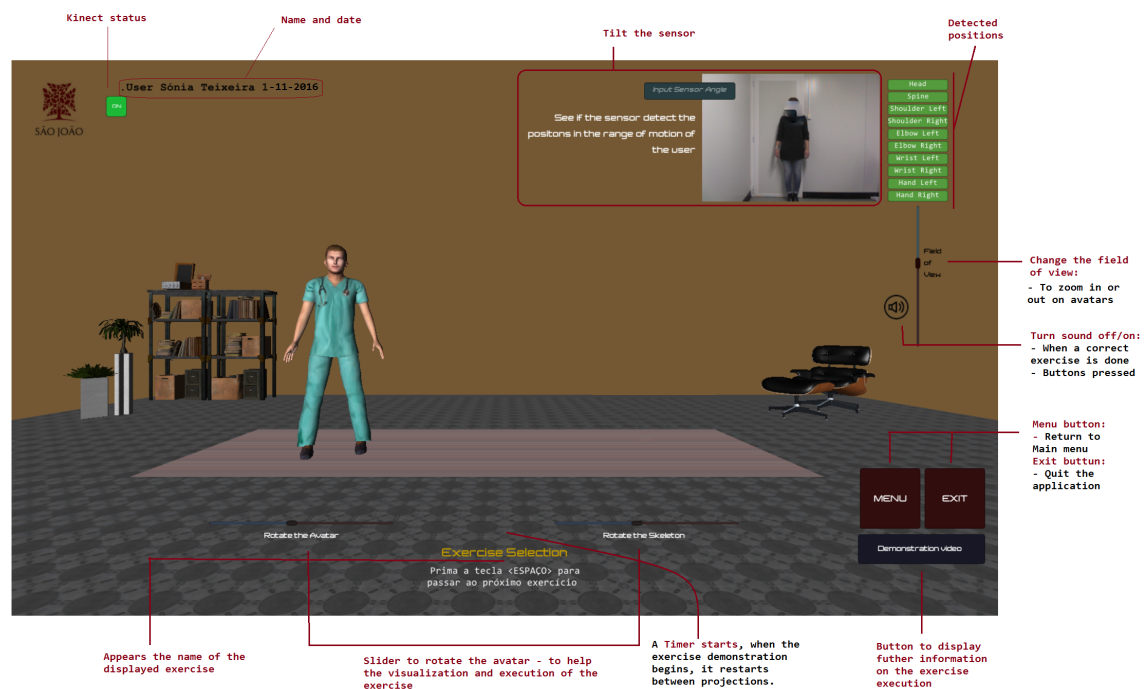


Figure 5.6: Description of the interfaces common components during game play

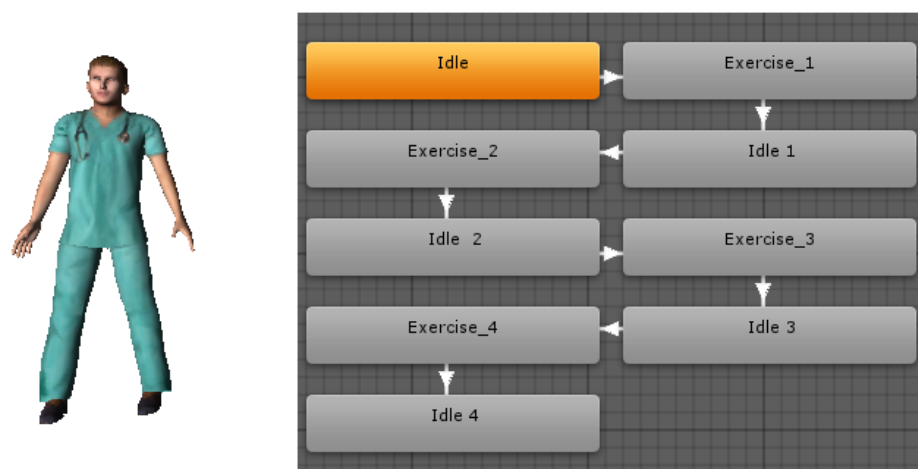


Figure 5.7: Illustration of the medic-avatar and its states

-Lastly, at the end of each session (see Figure 5.8), appears on the screen the following list of statistics, with the time spent on each exercise, number of exercises performed on each exercise and the average time spend in each exercise.

- Finally, a new session can be started by pressing the <Menu> button or quit the application by click on the <Exit> button.



Figure 5.8: Statistics

The number of exercises performed are counted using a sequence of simple steps for each exercise, based on the locations of skeletal joints and time. For a given exercise to be counted the following conditions need to occur:

- First of all, its fundamental to make sure that the skeleton joints involved in the exercise are being properly detected by the sensor;
- Then a series of distances are calculated and compared with pre-defined values, as an example for the fourth exercise (Figure 5.9) two distances are calculated in the yy plane (corresponds to the vertical plane) hand - elbow and elbow-shoulder;
- In case the distance values are superior then a pre-set value, a timer is started and if the user maintains for a determine period of time the condition above, an accomplished exercise is counted.

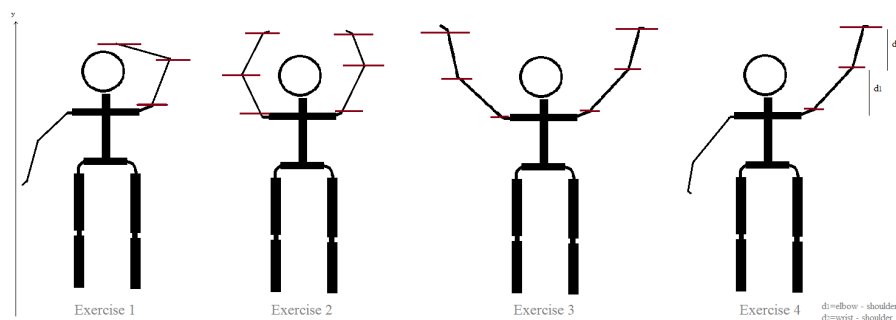


Figure 5.9: Exercise counter measures

Overall, these are the aspects that all the developed interfaces have in common. Now, will be presented each interface with emphasis on the type of visual feedback implemented (see Figure 5.10).

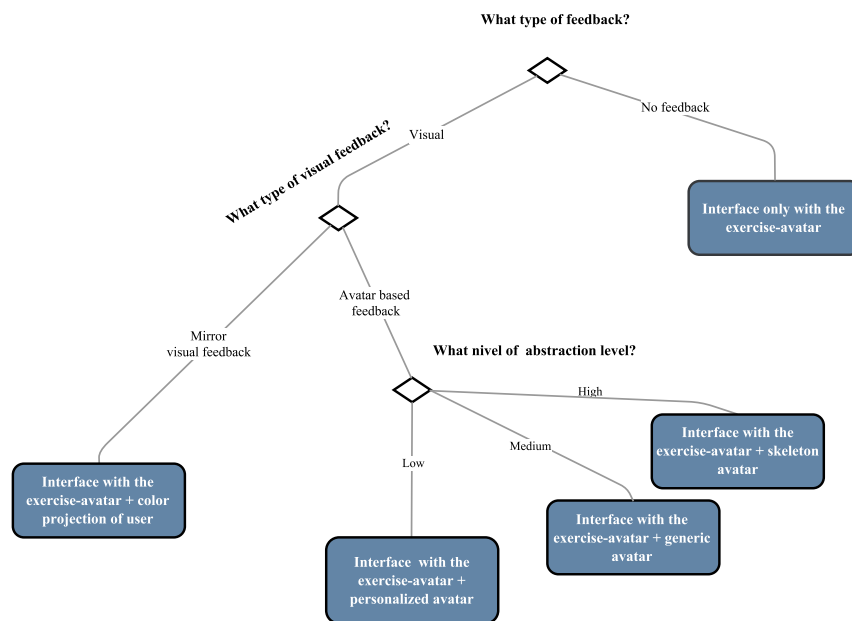


Figure 5.10: Decision tree for type of visual feedback

5.1.3.2 Interface with no visual feedback

The first interface developed had no visual feedback, only the medic-avatar is represented. A screenshot was taken before beginning the exercise (see Figure 5.11), the user can only see its projection in the beginning and between the intervals of the exercises for possible position adjustments relative to the sensor.

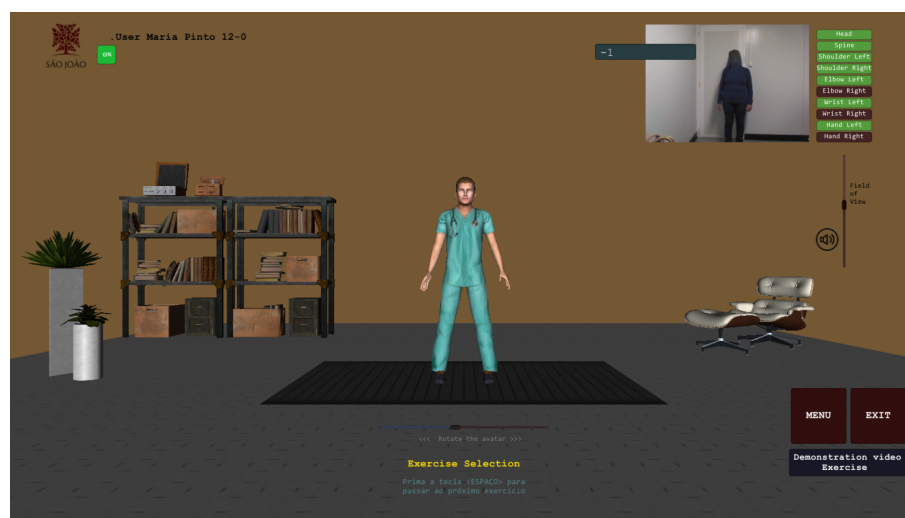


Figure 5.11: Interface with no visual feedback

5.1.3.3 Interface with mirror-based feedback

For this interface, a mirror-based feedback is implemented by displaying side-by-side the medic-avatar and the player, by using the RGB data from Microsoft Kinect (see Figure 5.12).

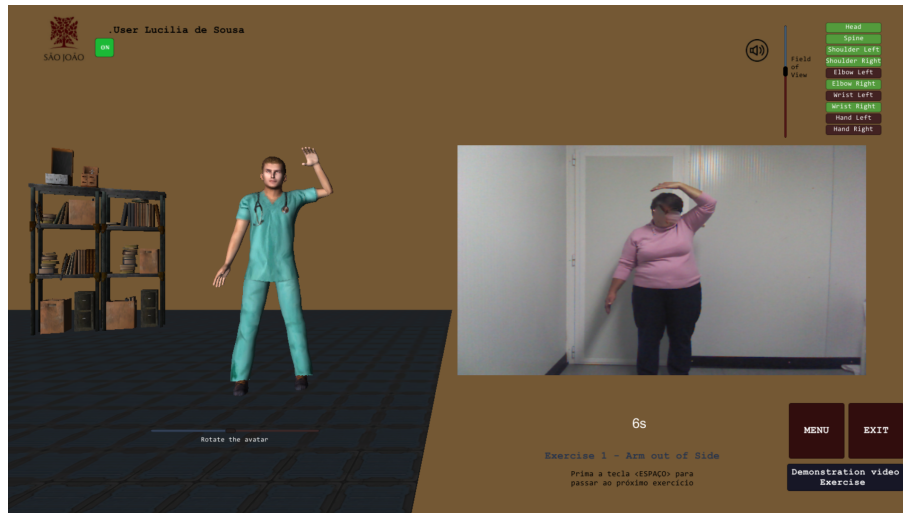


Figure 5.12: Interface with mirror-based feedback

5.1.3.4 Interfaces with avatar-based feedback

For the remaining interfaces, the visual feedback is avatar-based. Three non-customisable types of avatars were used for this study. Each avatar is rigged with a virtual skeleton (a total of 20 joints the same ones tracked by the Microsoft Kinect) and, the joints that are used during movement are mapped directly onto the values placed on the avatar puppet within the game world (see Figure 5.13). Also, facial features, such as the eyes and mouth remain fixed during the game play.

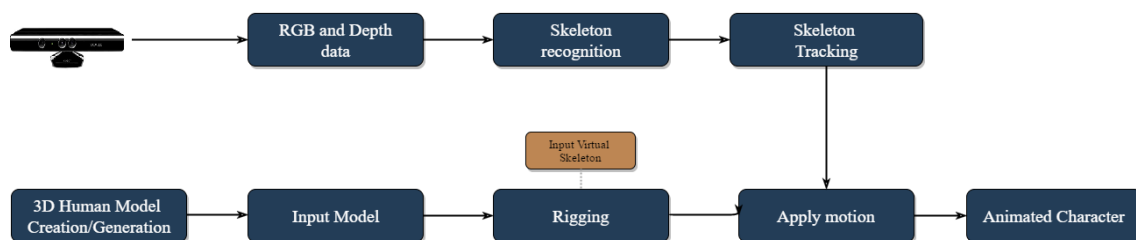


Figure 5.13: Block diagram system for animation of the player-avatar

In terms of visual appearance, the three avatars consisted of a (see Figure 5.14):

1. Skeleton avatar: This avatar was represented in the most minimalistic form with regard to its physical appearance (e.g. resembles a skeleton shape). As compared to the other two representations that were fixed in their physical dimensions, the skeleton avatar represented a direct match to the player's bodily form. The lack of graphical detail was felt to be an important component in understanding how well players could self-identify with its appearance.

2. Humanoid avatar: Designed to resemble the most human looking, it included proportionate body parts and facial features. It were customize and integrated in the game two different avatar with different features, most notable its genre and race.

3. Personalized avatar: Different levels of abstraction in an avatar-based situation were sought in this study, for a low level of abstraction the idea reside in the avatar resemble the player. In order to obtain this avatar, a 3D scanning of the player body is performed, resulting in a mesh followed by its rig with a virtual skeleton, so its possible in Unity treat it as a humanoid avatar. This process is explained in more detail in Appendix C.

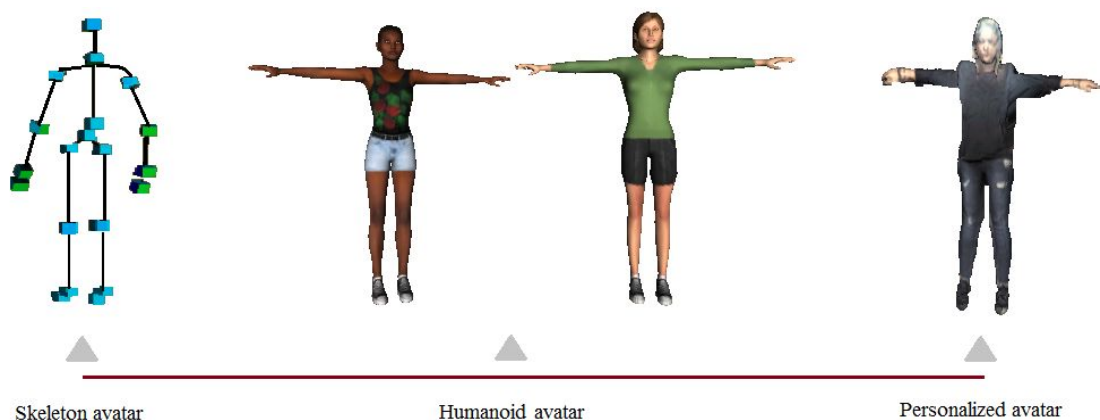


Figure 5.14: Examples of the available avatars with different levels of abstraction

For the interface with visual feedback based solely in avatars, followed the main menu appears an option to select one of the four available avatars (see Figure 5.15). In game play, the medic-avatar and the selected avatar are represented side-by-side during the entirely duration of the game (see Figure 5.16).

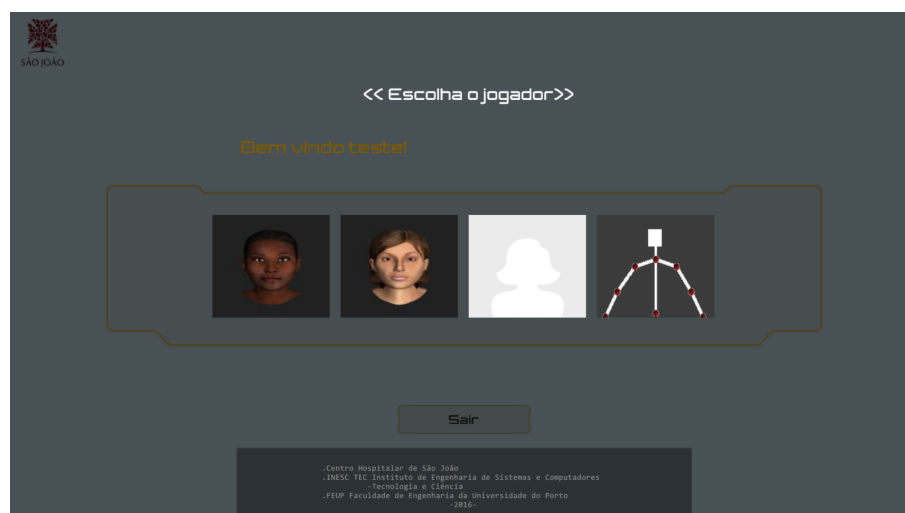


Figure 5.15: Interface components: Player selection

In order to evaluate the influence of displaying the medic-avatar and the player-avatar simultaneously, another interface was developed with avatar-based feedback, where the avatar activity occurs sparsely. In other words, this interface displays the exercise first, where the medic-avatar is the only visible. Then, the player-avatar appears alone (see Figure 5.17), the amount of time the medic-avatar appears is controlled by the user. Also, along the game a series of messages appear on the screen explaining the routine.

For interfaces with avatar-based visual feedback, to simplify and better understand the interactions between the interface and the user, it is present a Use Case Diagram (see Figure 5.18). Due to the complexity of the interface, the use cases were grouped into packets of subsystems.

In resume, the developed interfaces differentiate within each other in two distinct features (see Table 5.4):

- Player visual representation;
- Temporal activity between the medic-avatar and the player visual representation.

In the design period, the present interfaces seemed the more relevant for this study, given the fact the number of interfaces with different combinations of the features mentioned above between player visual feedback and temporal activity had to be taken into account, since the developed interfaces were all tested in the same session.

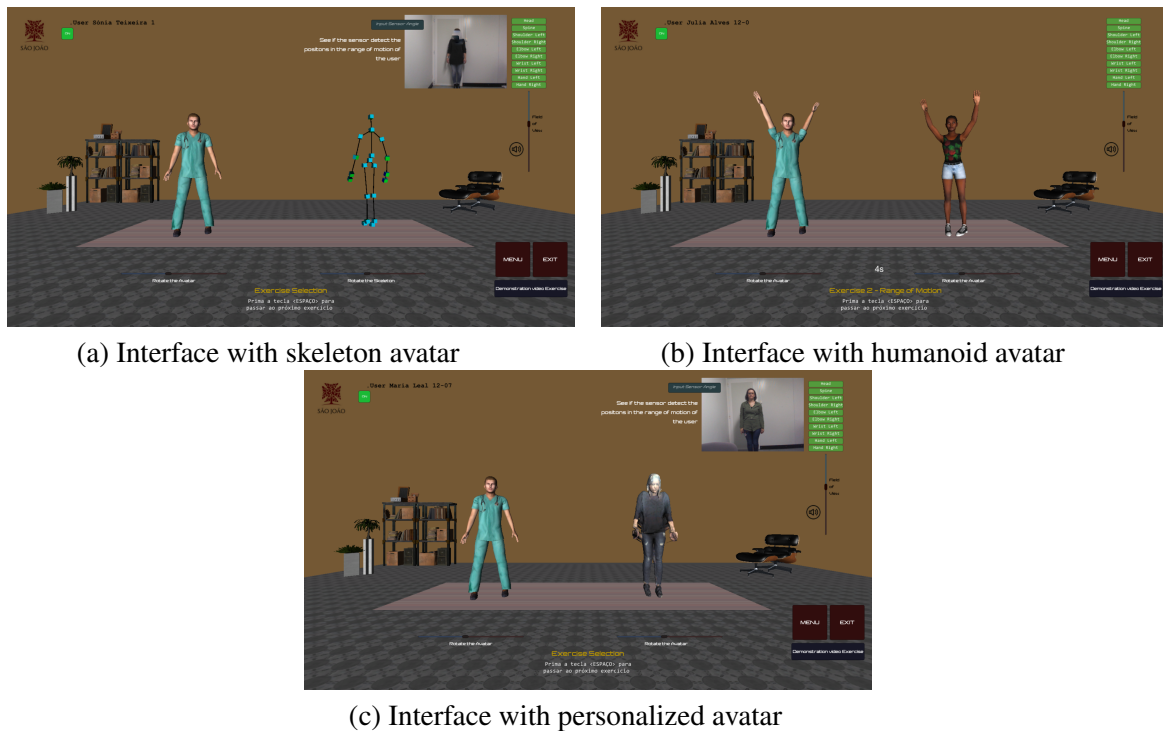


Figure 5.16: Interfaces screenshots for avatar-based feedback



Figure 5.17: Interface screenshot for avatar based feedback, with sparse activity between the medic-avatar and the player-avatar

Table 5.4: Type of visual and temporal representation in the developed interfaces

Interface	No visual feedback	Avatar-based feedback	Mirror-based feedback	Temporal activity
Interface with no visual feedback	x			Simultaneous
Interface with mirror-based feedback			x	Simultaneous
Interfaces with skeleton-based feedback		x		Simultaneous
Interfaces with humanoid avatar-based feedback		x		Simultaneous/Sparse
Interface with personalized avatar-based feedback		x		Simultaneous

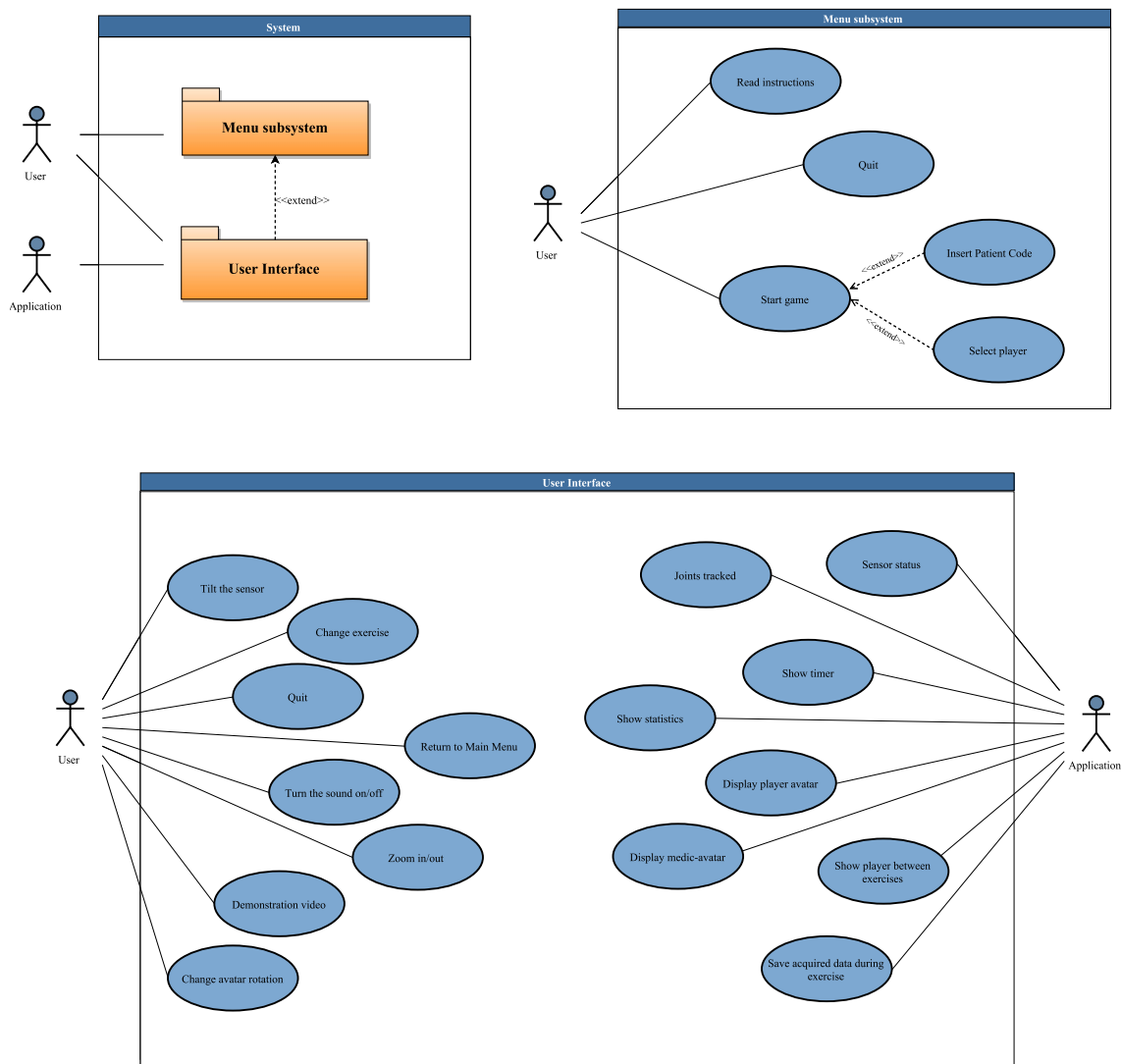


Figure 5.18: Interface avatar-based visual feedback: User packs and respective subsystem use cases

5.1.4 Questionnaire

The questionnaire used for this study is not based in one single standardized questionnaire but rather, by resorting to a collection of questionnaires, where parts or ideas are used leading to the creation of one (see Appendix E). The development process used in the proposed questionnaire is shown in Figure 5.19, the test period occur in Hospital S. João with a sample of four breast cancer survivors.

The main reasons for not use a standardized questionnaire revolve around the fact it was important to enquire the patients in different aspects, such as: usability, functionality, selection of the type of feedback provided within each interface, evaluation of the interaction with the virtual environment (VE) and possible modifications. Other important factor, was to keep the language as simple as possible and, the questionnaire concise due to the extension of the aspects to be evalu-

ated. A brief summary of available gaming scales with an overview of its strengths and drawbacks is shown in Table 5.6. This scales did not meet the requirements of this study, however it was an undisputed source of expiration in terms of structure, scale and focus areas.

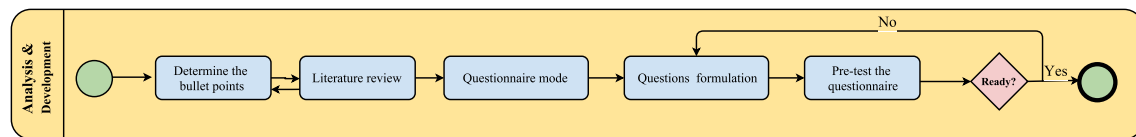


Figure 5.19: Diagram for questionnaire conception

The questionnaire consists of an overall eight sections, which are the following:

1) Authorization to use the information acquired in the process: This is a merely bureaucracy because an informed consent (see Appendix D) was provided in the begin of each session;

2) Characterization of population health: Here is done an overview of the health history and currently status of the patient. Focus primarily, in the treatments and secondary effects from breast cancer, this section has the avail of medical staff form Hospital S. João;

3) Demographic information: Main purpose is to describe the population, which can further be used to divide the population into different groups. For example, age, gender, marital status, academic degree, employment status, among others;

4) Relation with new technologies: Aims to gather information about the interaction with technological resources, more specifically what type of technological components the participant owns and how often plays on them;

5) Evaluation of the proposed interfaces: The main purpose of this section is to obtain the preferred interface, with the respective classification of each interface using a 5-point scale (see Figure 5.20). Also, assess the overall usefulness of the interfaces present in a home environment. This section of the questionnaire are based in [86, 87];

6) Relationship with the VE: In this section of the questionnaire, the opinion of the participants is sought in different topics such as functionality/performance of the overall system (focus on the avatars) and relationship with the VE, which is based in [88]. Another important aspect to assess, it is the immersion of the player in the virtual environment. For this purpose, part of the work present in [89] is use. This work focus on the concept of self-presence (see Table 5.5), which describes how oneself is elongated into virtual environment through virtual representations (avatars, for example).

7) Considerations / feelings after demonstration of interfaces: Based in the work of [90]. Assesses the game experience as scores in on the following components: immersion, flow, competence, positive and negative affect, tension, and challenge.

8) Suggestions: The last section of the questionnaire, consists in a list of suggestions that its implementation is doable in the existing interfaces, also has the option of an open response field.

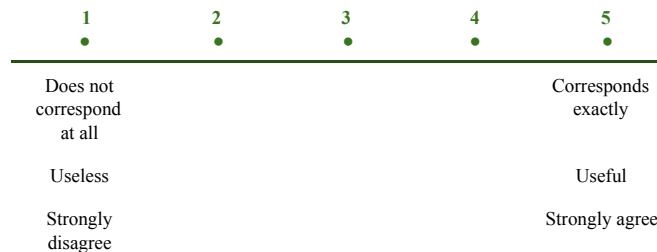


Figure 5.20: 5-point scales to three semantic differential pairs of adjectives

Table 5.5: Summary of the Proto Self-Presence Framework, (Adapted from [89])

Definition	The extent to which a media tool and corresponding virtual selfrepresentation are integrated into body schema.
High Self-Presence implies	Media tool feels and is treated like an extension of body. Body schema;
Relevant aspect of Self responses possible correlates	Time spent using VE; Level of technology expertise; Game genre.
Possible Causes	Extent of natural movements and natural (haptic) feedback afforded by media tool.
Sample Questionnaire Questions	<i>“When using the virtual environment, to what extent do you feel like your hand is inside of the virtual environment?”</i>

In sum, the questionnaire developed focuses on several aspects deemed essential for this work, such as performance, personal preferences (type of visual feedback, for example), integration with the VE and possible improvements in the applications presented, with regard to the participant state of mind, social conditions, involvement with new technologies and health status.

5.2 Data Collection

The experimental part of this research was conducted at Centro da Mama in Hospital S. João from the end of October until the beginning of December, 2016 (see Figure 5.21); with the environment of acquisition in Figure 5.22. Overall, thirteen days were dedicated to testing the interfaces with an average of 5.8 participants per day.

Each session took approximately 30 minutes, which evolved the test of the interfaces by the patient and subsequent filling of a questionnaire, resulting in acquisition of quantitative and qualitative data (see Figure 5.23).

Table 5.6: Strengths and Limitations of some Existing Gaming Scales, (Adapted from [91])

Questionnaire/Scale Name	Number of Items	Number of Subscales	Strengths	Limitations
Game Engagement Questionnaire (GEQ) (2009)	19	N/A	<ul style="list-style-type: none"> - Scale items are drawn from existing literature regarding key factors in game engagement - Scale covers aspects of immersion, presence, flow, psychological absorption, and dissociation - Scale was demonstrated to be a psychometrically strong measure of game engagement levels 	<ul style="list-style-type: none"> - Scale was designed to be used in research to understand the negative effects of violent video games - Scale measures only factors related to game engagement - Scale uses only three response options (“yes”, “maybe”, “no”) - Scale was administered mostly to middle school children and college-age, male frequent gamers
Game Experience Questionnaire (GEQ) (2008)	33	7	<ul style="list-style-type: none"> - Measures the gaming experience through seven dimensions (immersion, tension, competence, flow, negative affect, challenge, and positive affect) 	<ul style="list-style-type: none"> - Does not cover the usability aspect - Some items are too generic, and thus, difficult to interpret (e.g., “It felt like a rich experience”) - Has not been officially published in a journal, and thus, little is known behind methodology used to derive and validate the questionnaire
Gameplay Experience Questionnaire (2005)	19	3	<ul style="list-style-type: none"> - Measures the three key dimensions of immersion that contribute to the game-play experience - Games chosen in the evaluation of the questionnaire covered multiple genres (e.g., FPS, sports, simulation) - EFA was used to reduce the number of items on the questionnaire 	<ul style="list-style-type: none"> - Questionnaire was primarily designed to validate the SCI model - Questionnaire respondents were mostly young Finnish males - Some items on questionnaire did not translate well from Finnish to English (e.g., “I handled also my own emotions through the game”) - CFA was not employed to further validate the scale
Player Experience of Need Satisfaction (PENS) (2006)	22	44	<ul style="list-style-type: none"> - Measures motivation for computer game play in relation to enjoyment - Based on existing theory of human motivation (i.e., self-determination theory) - PENS model has been demonstrated to predict fun, value, and sustained engagement in some video games 	<ul style="list-style-type: none"> - Mostly focuses on motives for game play in terms of competence, autonomy, and relatedness factors - Factor analysis was not employed to validate the scale - Proprietary information and costs money to use for game companies

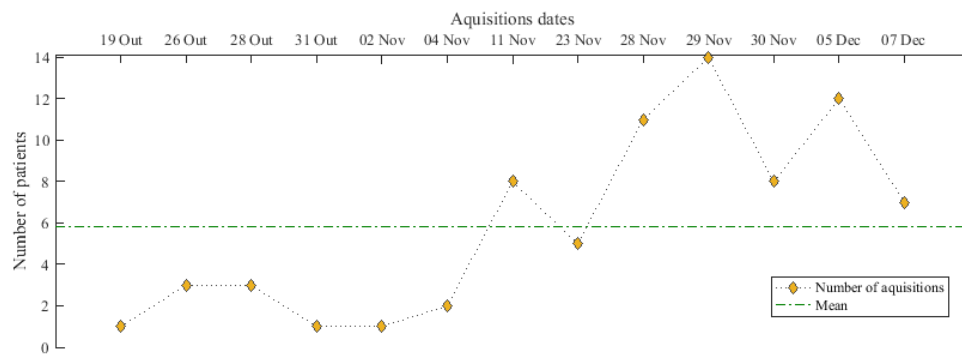
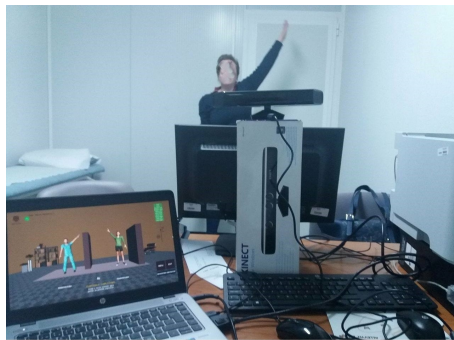
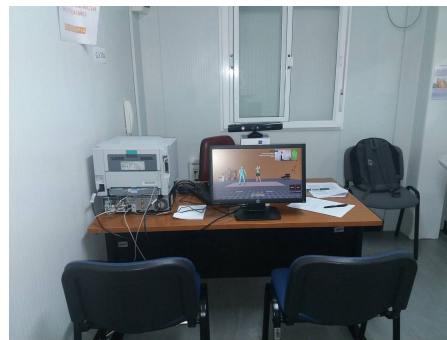


Figure 5.21: Number of sessions performed per day



(a) Kinect position



(b) Perspective of the user

Figure 5.22: Acquisition environment

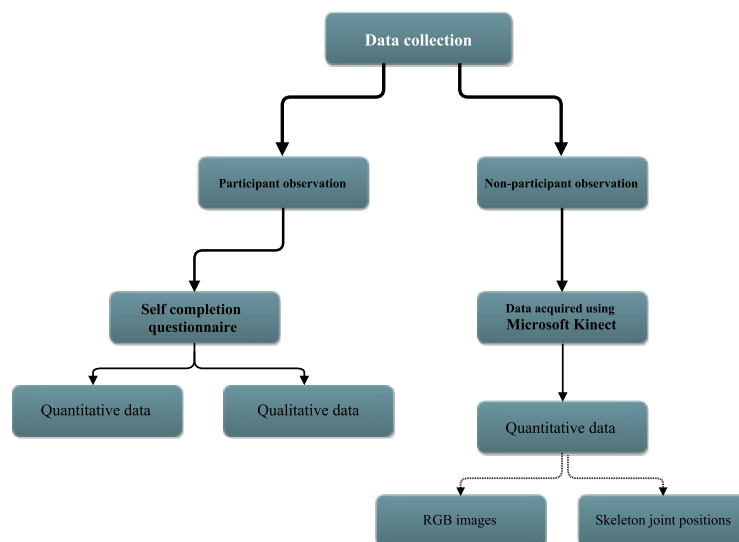


Figure 5.23: Data acquisition scheme

5.3 Results and Discussion

In this section, it is present the analyse of the questionnaire responses and, some considerations are made along the way. In this section, the information considered the most relevant is shown, the rest are in the Appendix F. The feasibility of this study was tested in 4 patients, then the different interfaces and subsequent filling of the questionnaire were tested in 72 patients with breast cancer.

5.3.1 Demographic information

In this part of the questionnaire, general information about the participants in this study is overviewed (see Table 5.7), such as: height, weight, age, marital status, academic level and professional status.

Table 5.7: Questionnaire information: Brief summary of the sample tested

Sample size	Age		Height		Weight	
	Mean (M)	Standard deviation (SD)	M	SD	M	SD
72	57.79	11.16	1.58 m	0.05	65.99 kg	12.08

Ages over 60 represent 51.39% of the test subject. The breast prevalence rate (see Table 5.8) highest in people between 60 - 69 years and 40 - 49 years with a rate of 37.50% and 26.39%, respectively. The study population presents, for the most part, a level of schooling below the minimum educational level (see Table 5.9), more specifically 65.27%.

Table 5.8: Questionnaire information: Age ranges of the study population

Age distribution	Percentage	Breast cancer prevalence rate	Percentage
30 - 39 years	4.17%	60 - 69 years	37.50%
40 - 49 years	26.39%	40 - 49 years	26.39%
50 - 59 years	18.06%		
60 - 69 years	37.50%		
70 - 79 years	12.50%		
80 - 89 years	1.39%		

Table 5.9: Academic status

Responses	Occurrences	Percentage
4th grade	34	47.22%
6th grade	6	8.33%
9th grade	7	9.72%
12th grade	10	13.90%
Old bachelor's degree	5	6.94%
Bachelor's degree	9	12.50%
Master's degree	1	1.39%

5.3.2 Characterization of population health related with breast cancer

An analyse of the treatment applied to each patient was necessary to do, given the fact that problems related with of ROM is a direct effect from the applied treatment. This part of the enquiry, started with the type and location of the surgery performed on the breast and axil. The most common surgery performed on the breast (see Table 5.10) was a variant of conservative surgery with 55.55%. And, 88.88% underwent surgery in the axillary region (see Table 5.11). Then, it was inquired the performed treatments (see Table 5.12), such as:

- Chemotherapy sessions are quite even done by 54.17% of the study population;
- Radiotherapy the vast majority performed radiotherapy (75%);
- Physiotherapy the majority of study participants did not undergo physical therapy as a follow-up treatment.

Table 5.10: Questionnaire information: Type of surgery performed during treatment

Type of breast surgery			Type of axillary surgery		
Responses	Occurrences	Percentage	Responses	Occurrences	Percentage
Simple conservative surgery	34	47.22%	Axillary deflation	26	36.11%
Mastectomy			No surgery	8	11.11%
with reconstruction	19	26.39%	Sentinel ganglion	38	52.78%
Conservative surgery					
(with breast reduction)	6	8.33%			
Mastectomy					
without reconstruction	13	18.06%			

Lastly, it was assess the complications during treatment (see Table 5.13). The large majority did not develop any kind of complications during treatment. And, at this moment in time, just 12.5% of the participants developed lymphedema (see Table 5.14).

Table 5.11: Questionnaire information: Chemotherapy, Radiotherapy and Physiotherapy

Responses	Chemotherapy		Radiotherapy		Physiotherapy	
	Occurrences	Percentage	Occurrences	Percentage	Occurrences	Percentage
Yes	39	54.17%	54	75%	27	37.50%
No	33	45.83%	18	25%	45	62.50%

Table 5.12: Questionnaire information: Complications during treatment

Complications developed from surgeries			Lymphedema		
Responses	Occurrences	Percentage	Responses	Occurrences	Percentage
No	63	87.50%	Yes	9	12.50%
Hematoma	2	2.78%	No	63	87.50%
Thrombosis	1	1.39%			
Infection	2	2.78%			
Seroma	2	2.78%			
Hemorrhage	2	2.78%			

5.3.3 Relation with new technologies

One important aspect of this work, it is to ascertain the relationship of the participants with new technologies, for example gather information about what type of technological resources possess, the frequency of game play and free time for recreational activities.

The study population had no previous contact with serious games (see Figure F.4, Appendix F). It was determined that half of the participants does not have technology resources at home (see Figure F.1 and for more specificity Table F.5, Appendix F) and, for those who have technology resources at home the frequency of playing video games is very low or non-existent (Table 5.13). The majority rates free time for hobbies with highest marks (Table 5.14).

Table 5.13: Frequency on game play

Responses	Occurrences	Percentage
Never	12	16.67%
Once or twice a month	14	9.72%
Once or twice a week	12	8.33%
Every day	4	5.56%
No resources	36	50%

Table 5.14: Free time evaluation

Evaluation	Occurrences	Percentage
1	12	16.67%
2	14	19.44%
3	12	16.67%
4	20	27.78%
5	14	19.44%

5.3.4 Evaluation of the proposed interfaces

The evaluation of the proposed interfaces is one of the main focus of this study, where personal preference of the visual feedback, the temporal activity of events and mechanical aspects are the emphasis of this part of the questionnaire.

A large majority answered "yes" when asked if they would use any of the interfaces presented as a method of rehabilitation at home (see Figure 5.24). Among patients who underwent physiotherapy, the choice "yes" has a lot of adherence. However, a even high percentage from patients who did not perform physiotherapy, with a classification of 84.44% (see Table 5.15).

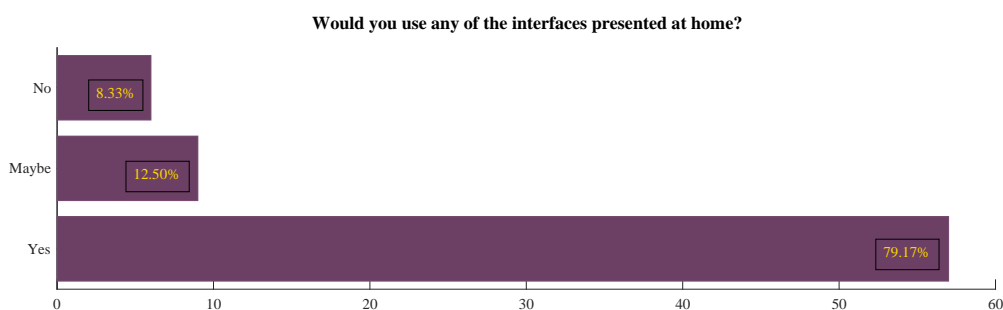


Figure 5.24: Questionnaire information: Using the favourite interface at home

Table 5.15: Questionnaire information: Use at home according to patients with or without physical therapy

Physiotherapy	Yes		Maybe		No	
	Occurrences	Percentage	Occurrences	Percentage	Occurrences	Percentage
Yes	19	70.37%	5	18.52%	3	11.11%
No	38	84.44%	4	8.89%	3	6.67%

In choosing the preferred interface there is no obvious winner, three of the six interfaces are virtually tied (see Figure 5.25). The most vote interfaces are the following:

- Skeleton-avatar feedback with 29%;
- Humanoid-avatar feedback with 28%;
- No visual feedback with 28%.

Nevertheless, information about the type of visual feedback can be extracted. For example, 72% of the votes fall back in interfaces with visual interfaces which 64% are avatar-based. Of note, it is the low choice of the interface with the medic-avatar and the player-avatar shown sparsely, with only 1%. The reason for this result, may be caused by the distinct workflow of this interface when compare to other interfaces, which culminates on the player spending more time adjusting to the interface.

Overall, all the interfaces received mostly the highest evaluations as can be seen in Figure 5.26. Although, the interfaces have very similar results, the skeleton-avatar interface has the more votes with evaluation of 5. It outperforms the humanoid-avatar slightly, possible justifications may be solely justified by:

- The personal preference of the avatar falls in a low level of abstraction;
- Problems with the avatar movement, for instance: the position of the avatar hands when the sensor can detected it properly (when the hand of the player is in front of the torso, for example). In this situation, the hands take a wrong position for the humanoid and personalized avatar. Whereas, the skeleton-avatar just turns the face of the cube.

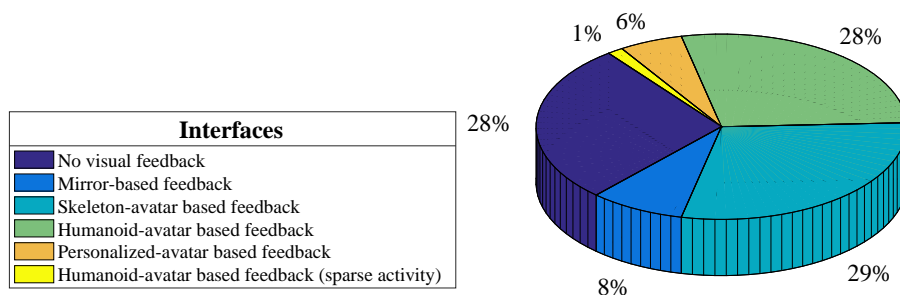


Figure 5.25: Questionnaire information: Interface preference

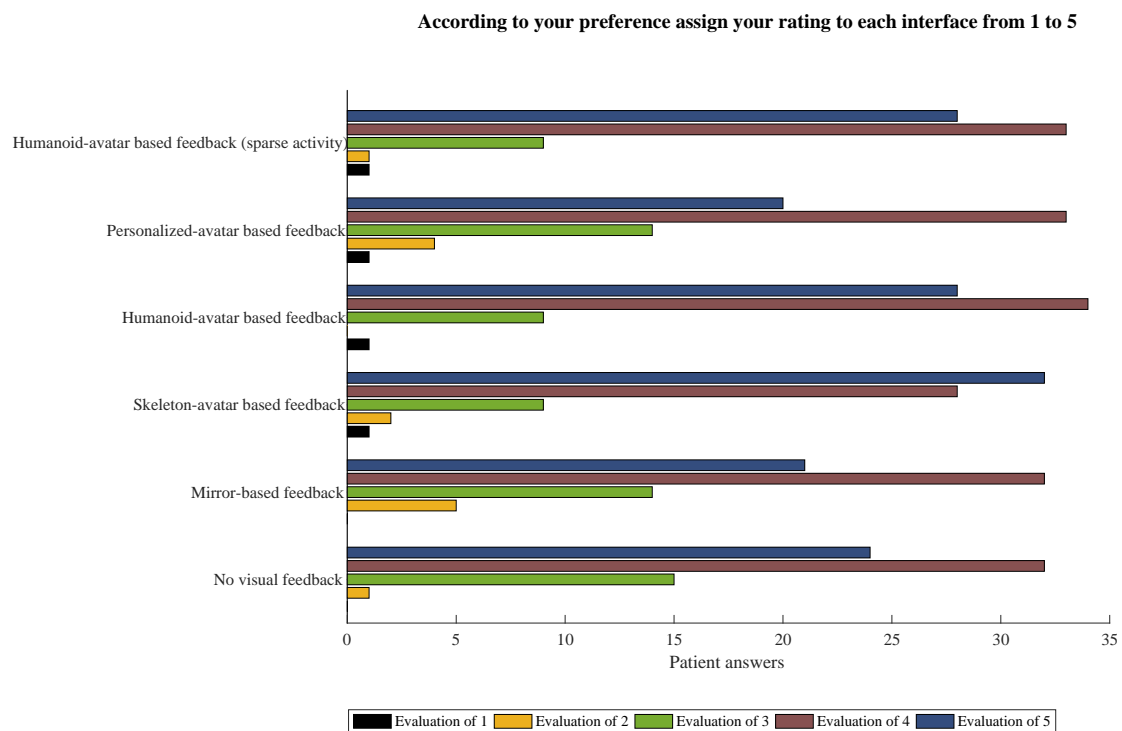


Figure 5.26: Questionnaire information: Interface evaluation

Mechanical features are a very important factor to assess because it can disrupt all of the other aspects. For example, if the exercises performed by the medic-avatar is not adequate it influences the overall engagement with the game. The large majority of test subjects evaluate the speed as normal (see Table 5.16) and 97% evaluate with a positive rate the movement replicated by the avatar (see Figure 5.27).

Table 5.16: Questionnaire information: Speed of the exercises

Responses	Occurrences	Percentage
Normal	66	91.67%
Fast	2	2.78%
Slow	3	4.17%
Very slow	1	1.39%

When asked to evaluate if the interfaces helped to have notion of the movement effected (see Figure 5.28) the interfaces with visual feedback were largely rate with "helped", with the mirror-based feedback interface evaluated as the most helpful, with the rest as a close second.

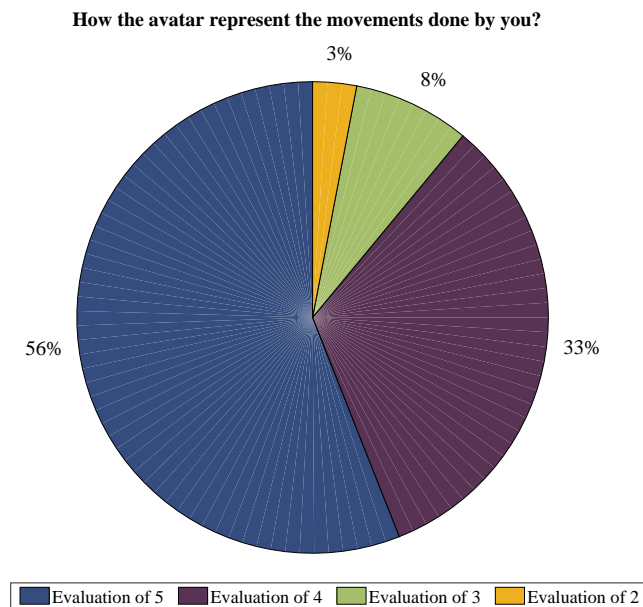


Figure 5.27: Questionnaire information: Representation of the movement by the avatar

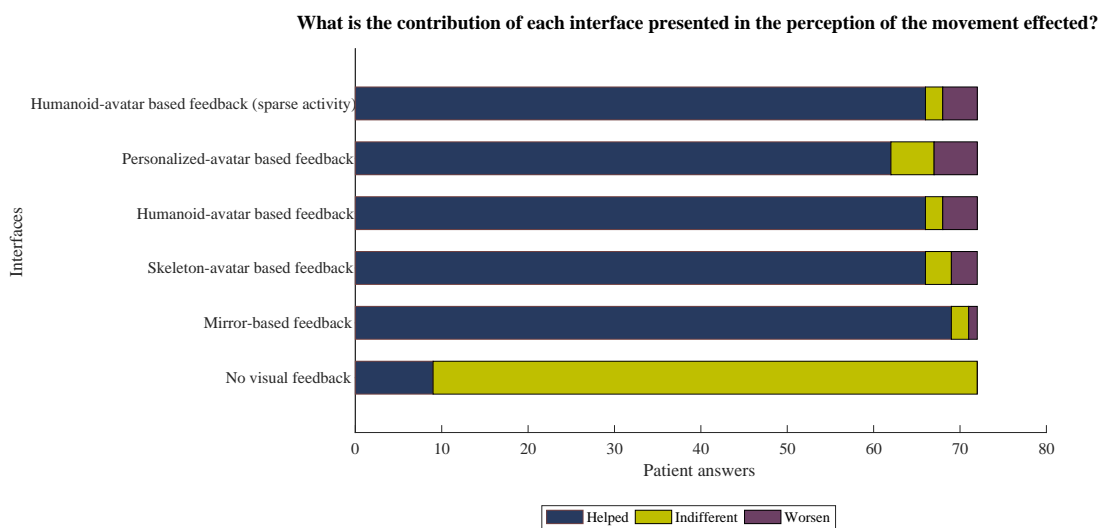


Figure 5.28: Questionnaire information: Perception of movement

Certain features were selected to further evaluate the preference of the tested interfaces, such as: physiotherapy, age, academic level and technological resources use.

For subjects who did physiotherapy (see Figure 5.29) the interfaces with skeleton-avatar based and no visual feedback are the most voted and, for the others humanoid-avatar based feedback interface is the preferred one.

According to patients age ranges (see Figure 5.30), the age intervals with more subjects are

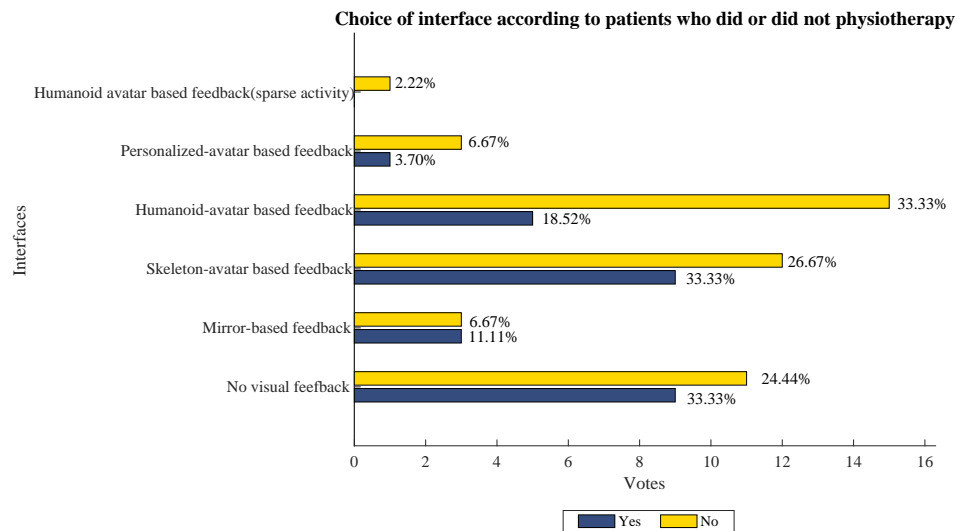


Figure 5.29: Questionnaire information: Choice of interface according to patients who did or did not physiotherapy

[60 - 69] and [40 - 49] where humanoid-avatar based and skeleton-avatar based interface are the preferred ones, respectively.

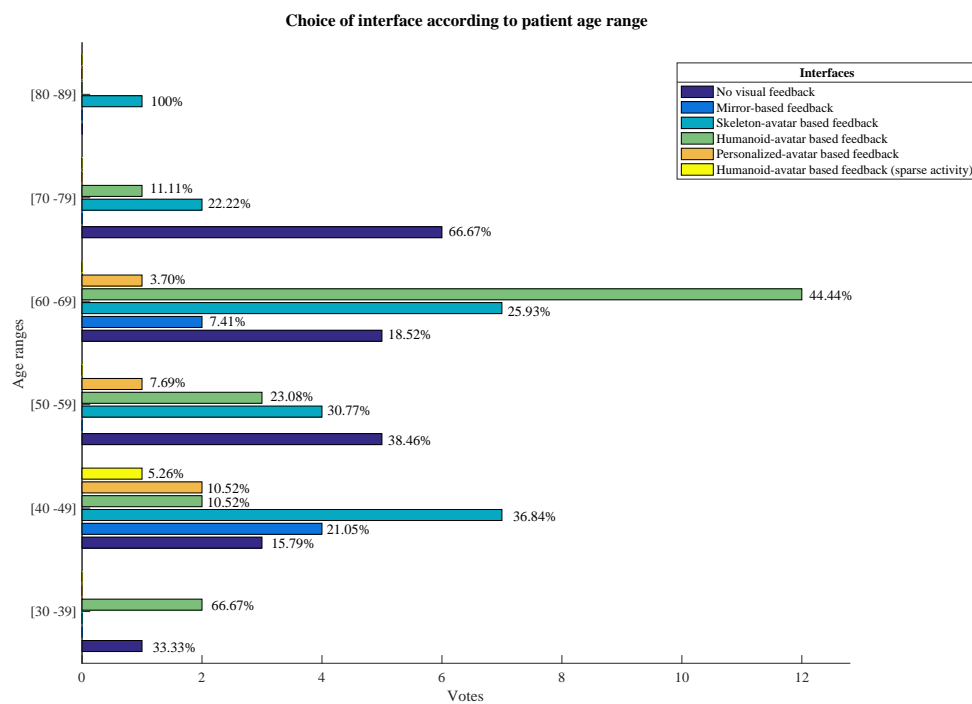


Figure 5.30: Questionnaire information: Choice of interface according to patient age range

For academic level (see Figure 5.31), the vast majority of the patients has the 4th grade as academic level. In this group, the avatar-based feedback interface was selected with 35.29% of the votes, followed by the interfaces: no visual feedback (34%) and skeleton-avatar based (23.53%).

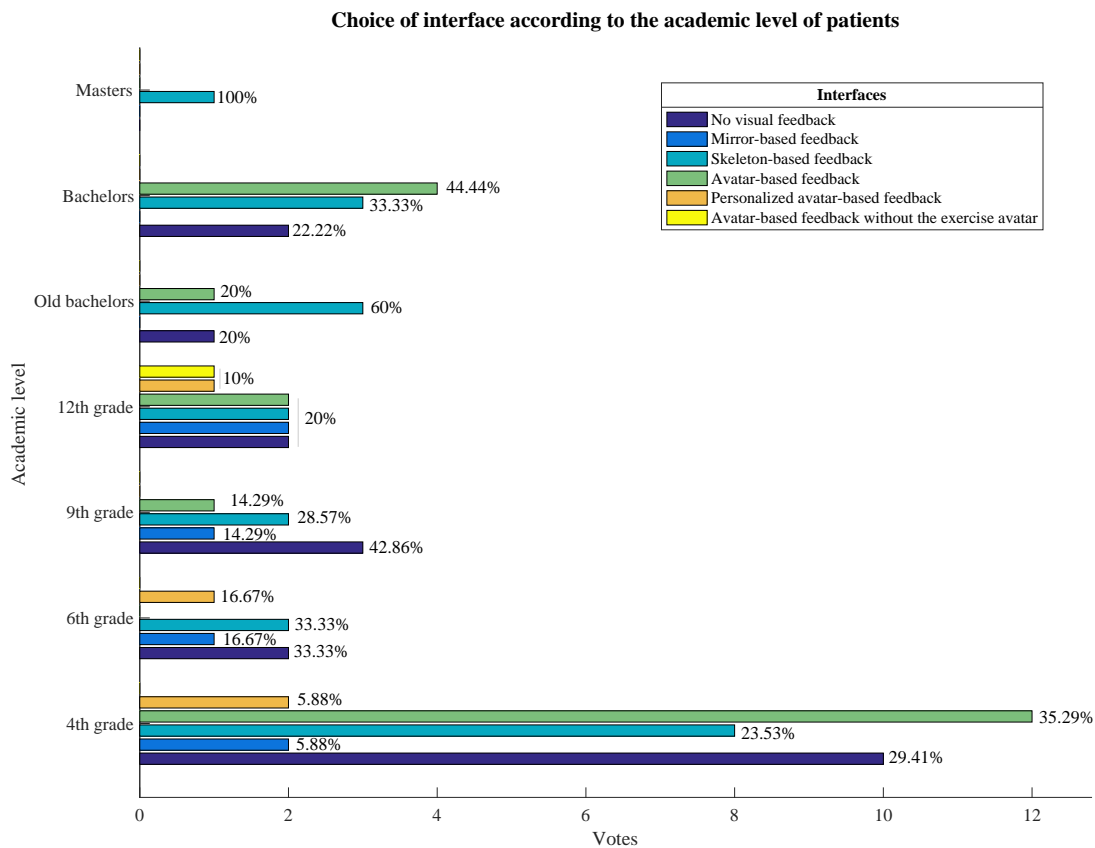


Figure 5.31: Questionnaire information: Choice of interface according to the academic level of patients

Lastly, the use of technological resources (Table 5.17) is even between the participants. Interfaces with visual feedback is preferred with 60.96% and 66.59% for subjects with and without technological resources, respectively.

Table 5.17: Questionnaire information: Type of visual feedback according to patients who use or not technological resources

Technological resources	Interface without visual feedback	Interface with visual feedback	Overall
Yes	39.04%	60.96%	50%
No	33.41%	66.59%	50%

5.3.5 Relationship with the virtual environment

The "self" concept has grown increasingly important in interactive media environments [92]. This part of the questionnaire investigated self-related processes in an avatar-based game. A key feature of the Microsoft Kinect is its motion-sensing capability that empowers players to manipulate and interact with items on-screen via movement.

In this part of the work, its study the integration of the user in the VE and its relationship with the controlled avatar. Hence, using the concept of self-presence introduced in the questionnaire section. Which is based on a standardized questionnaire: Self-Presence Questionnaire (SPQ) [89], whereas Self-presence is described as one is extended into virtual environments through its virtual self representations. As a note, the work of Jin and Park [92] describes self-presence as the connection between an individual's and an avatar's physical representation and movements.

From the questionnaire responses the following information were obtained:

- When asked if the avatar feels like an extension of the user body (see Table 5.18) 87.5% rates with a positive scale (with 50% rated with very high classifications).
- Immersion in the VE (see Table 5.19) is valued at 70.83% with the highest rankings, with 89.11% rated with a positive scale.
- When asked if the avatar feels part of ones body (see Table 5.20) or when something happens to the avatar body(see Table 5.21), the ratings are in the large majority positive, with 80,55% and 81.95%, respectively.

Furthermore, several aspects can influence the participant immersion in the VE. For instance, two important aspects are worth mention: the movements done by the player-avatar and, the frequency in playing computer games.

The participants who evaluate the movements of the avatar in a positive note have a median higher compared to those who evaluate negatively the movements of the avatar. Noticeable, the player's immersion tends shift towards higher ratings as the avatar's movement evaluation increases (see Figure 5.32).

Regarding the frequency in playing games, for those o never play its median and maximum is in a a rating of 5 for immersion in the VE (see Figure 5.33). For those who play everyday or, once or twice a week its median is 4, which also is its minimum. The results for those how play once or twice a week the evaluations are quite sparse.

In conclusion, the overview of the results incur in this section, it is notorious a high self-presence [89]. Which implies that the avatar feels and is treated like an extension of body. In the work this section was based, the possible cause point out for this result is the extent of natural movements and natural feedback afforded by the media tool.

Table 5.18: Questionnaire information: When playing the game/using the virtual environment, how much do you feel like your avatar is an extension of your body within the game/virtual environment?

Responses	Occurrences	Percentage
Evaluation of 1	2	2.78%
Evaluation of 2	7	9.72%
Evaluation of 3	27	37.50%
Evaluation of 4	30	41.67%
Evaluation of 5	6	8.33%

Table 5.19: Questionnaire information: When playing the game/using the virtual environment, to what extent do you feel inside of the game/virtual environment?

Responses	Occurrences	Percentage
Evaluation of 1	3	4.17%
Evaluation of 2	5	6.94%
Evaluation of 3	13	18.06%
Evaluation of 4	28	38.89%
Evaluation of 5	23	31.94%

Table 5.20: Questionnaire information: When something happens to your avatar's body, to what extent does it feel like it is happening to any part of your body?

Responses	Occurrences	Percentage
Evaluation of 1	5	6.94%
Evaluation of 2	8	11.11%
Evaluation of 3	26	36.11%
Evaluation of 4	28	38.89%
Evaluation of 5	5	6.94%

Table 5.21: Questionnaire information: When playing the game/using the virtual environment, how much do you feel your avatar is a part of your body?

Responses	Occurrences	Percentage
Evaluation of 1	4	5.56%
Evaluation of 2	12	16.67%
Evaluation of 3	26	36.11%
Evaluation of 4	25	34.72%
Evaluation of 5	5	6.94%

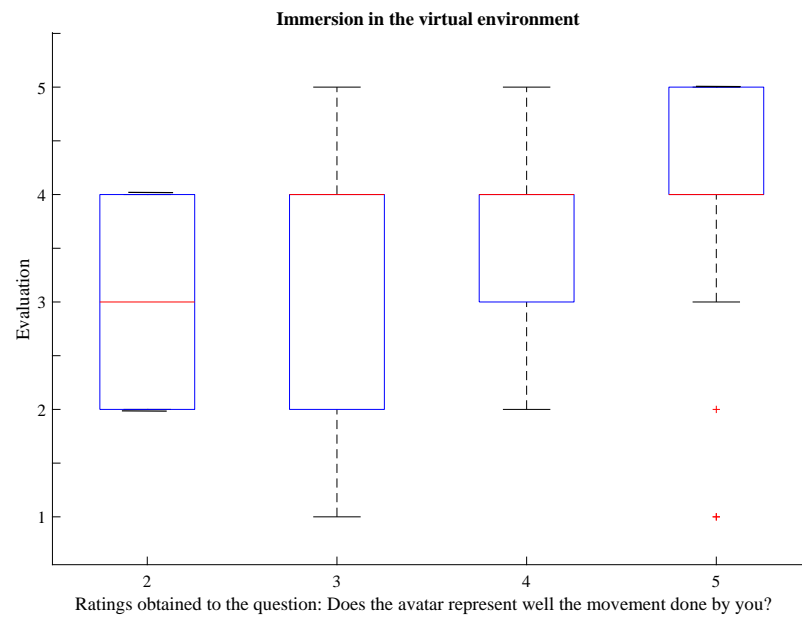


Figure 5.32: The boxplot shows the median evaluation for immersion in the virtual environment per rating on the avatar representation of the user. For those evaluate with 2 the representation of the avatar movement, the median is 3 with a maximum of 4 and a minimum of 2. Coinciding with the 3rd and 1st quartiles, respectively.

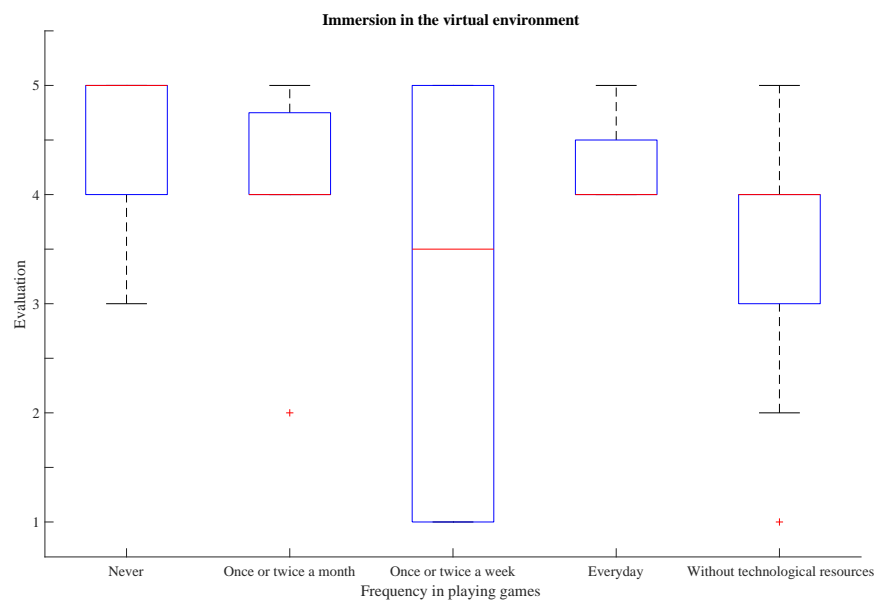


Figure 5.33: The boxplot shows the median evaluation for immersion in the virtual environment per frequency in playing games. For those who never play the median is 5, the maximum evaluation is 5 (coinciding with the 3rd quartile) and the minimum evaluation is 3.

5.3.6 Considerations / feelings after demonstration of interfaces

An important aspect to take in consideration is the state of mind of the participants because it is key to find out if there are no external factors who may influence the overall results. For this purpose, in this section of the questionnaire, it was asked to select three out of fourteen options. In general, all patients rated the experience positively and enriching (see Appendix F, Table F.6).

5.3.7 Suggestions about the interfaces presented

The last part of the questionnaire, focused on possible improvements / additions to the interfaces, where a list of suggestions and an open response field were presented. The vast majority replied (see Table 5.22) that had nothing to suggest. From the possible suggestions, the options to play with more than one player and more information during the game execution, formed the most voted with 26.39% and 12.50%, respectively.

Table 5.22: Questionnaire information: Suggestions choices

Suggestions	Number of votes	Percentage
No suggestions	33	45.83%
Option to perform the exercises with one more player (multiplayer)	19	26.39%
At the end of each exercise, the option to visualize the movements made by the user	4	5.56%
More information about user performance during exercise execution	9	12.50%
Option to choose different avatars	2	2.78%
Choice of different virtual environments	4	5.56%
More support information while playing the game	1	1.39%

5.4 Additional work

After the evaluation of the interfaces, later work was done in order to improve specific aspects of the interfaces. In this section, its present multi-player mode, an option added in the avatar-based interfaces. The main reasons to implement multi-player mode comes from the fact it was the most voted suggestion in the questionnaire. And, the doctor who followed the testing process also had suggested it for further sessions.

For multi-player mode, two distinct interfaces were implemented with avatar-based visual feedback, more specific the humanoid-avatar (see Figure 5.34a) and skeleton-avatar (see Figure 5.34b). As previous mention in Chapter 3, the Microsoft Kinect can detect up to 8 individual but is just able to follow 2, thus the multi-player mode is restricted to two players at a time.

In order to facilitate the differences between the interface for a game or two players, a diagram is presented with the system packages and respective use cases (see Figure 5.35).

However, a problem arises if during the execution of the game for some reason the sensor does not recognize both users for a period of time, which can lead to swap of avatars. Consequently, the acquired data would be corrupted.



(a) Humanoid-avatar

(b) Skeleton-avatar

Figure 5.34: Interface with avatar-based feedback for multi-player

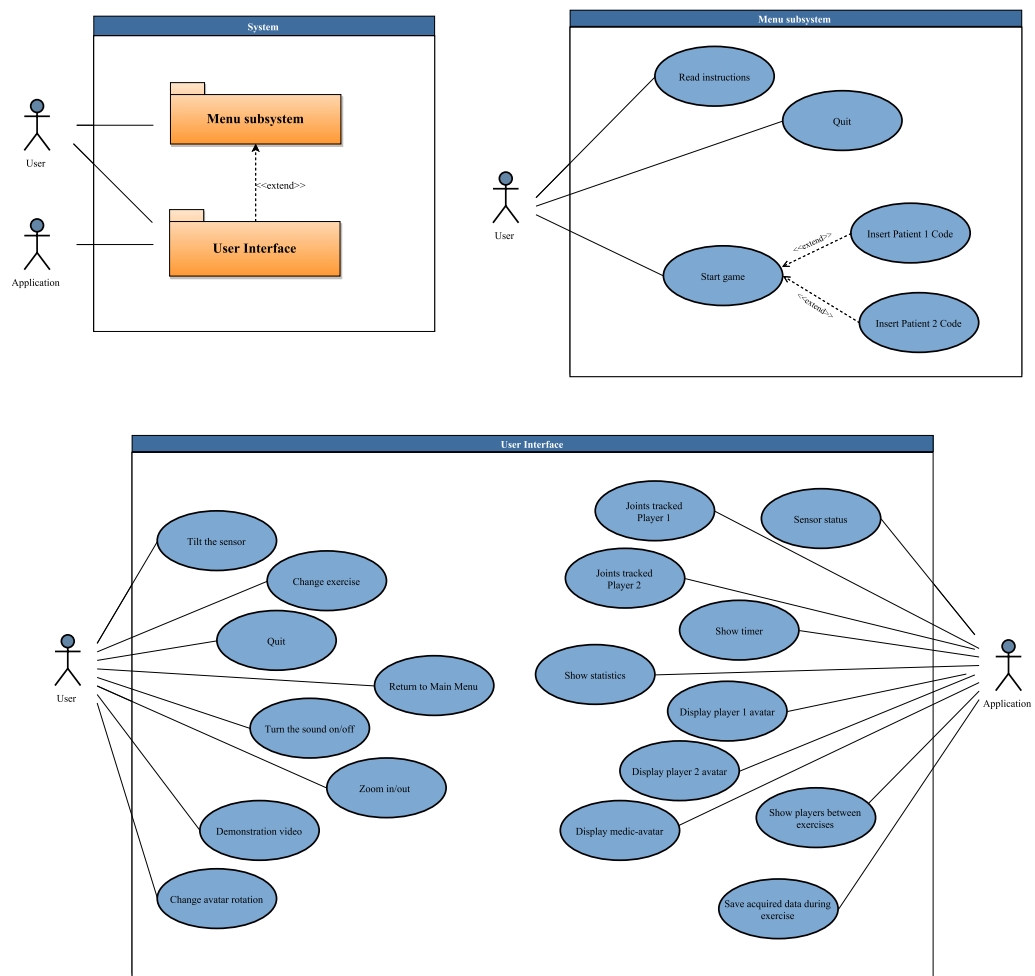


Figure 5.35: Multi-player interface with avatar-based visual feedback: User packs and respective subsystem use cases

5.5 Summary

In this chapter, it were described a series of interfaces developed for the rehabilitation period of breast cancer patients. The interfaces were tested in sessions performed with a sample of breast cancer survivors, where a questionnaire were fill by the participant at the end of each session. Then, a further assessment was performed by the analyse of the questionnaires.

Several features were depicted in the evaluation period. Such as, implementation aspects like the velocity of the medic-avatar and the player-avatar behaviour. There was no major problems point out during trial test or the sessions conduct in a clinic environment. It was of extreme importance that aspects related with functionality and fluidity of the game did not pose problems, since this is directly correlated with other aspects studied such as integration of the user on the VE.

In the design period, it was decided that all the interfaces must have the same visual background, features and fluidity so, the target aspects to evaluate are the only major noticeable change. The major changes that occur from interface to interface are the visual and temporal representation of the user. For the visual representation of the user, it is categorized into visual and non-visual, where in the visual category are presented several avatars with different levels of abstraction and video projection of the user. By the data obtained, the overwhelming majority with about 88.89% preferred an avatar form as visual feedback oppose to have a mirror-based feedback. One reason that may contribute to this outcome, may be the fact most woman affected by breast cancer are often subject to physical, emotional and social discomfort [93].

The most voted suggestions led to the implementation of an multi-player interface, in which the options were humanoid-avatar or skeleton-avatar. During the test period and the results obtain, features related to player performance were pointed out as possible additions to the interface. For the type of exercises performed, the following aspects were selected: time, number of exercises performed and the angles of the shoulder and elbow. Time and the number of exercises is already implemented. However, the later is not very reliable because it is implemented from a set of measures. To calculate angles, it is necessary to know beforehand if the Microsoft Kinect has enough accuracy. In this regard, the work that followed was an analyse of the reliability of Microsoft Kinect (Chapter 6) and a study in recognition of human activity (Chapter 7).

In short, the results were all-around very satisfying. Overall, the interfaces were well received by the test population, been considered as a possible method for rehabilitation of breast cancer patients. The majority of the participants elected the interface with avatar-based visual feedback as their favourite. The design of this particular interface meets the following objectives:

- Provides a detailed and visual guide on the correct movements for each exercise;
 - Captures the actual movements of the patient for real time display as well for post-exercise review;
 - Provides intuitive feedback to the patient regarding the quantity and time consuming.
- Hence, the interface avatar-based was selected to be used for future sections in Hospital S. João.

For this purpose, some modifications were done regarding the input of medical staff, which were the following :

- The exercises are displayed in three consecutive rounds, the medical staff reason that each exercise should be repeated 10 times each round;
- All the exercises should be performed with both arms, the medic-avatar was animated accordingly.

For this part of the work as a form of conclusion, it was applied the taxonomy used in Serious Games for Rehabilitation [71] reviewed in Chapter 4 for all the implemented interfaces (see Table 5.23).

Table 5.23: Classification of the implemented interfaces using the Taxonomy of Serious Games for Rehabilitation

Interface	Application Area	Interaction Technology	Game Interface	Number Players	Competitive/ Collaborative	Game Genre	Adaptability	Progress monitoring	Performance feedback	Portability
No visual feedback	Motor	Body movement + Keyboard	3D	Single	None	Movement Simulation	No	Yes	No	Home
Mirror-based feedback	Motor	Body movement + Keyboard	3D	Single	None	Movement Simulation	No	Yes	Yes	Home
Avatar-based feedback (sparse activity)	Motor	Body movement + Keyboard	3D	Single	None	Movement Simulation	No	Yes	Yes	Home
Avatar-based feedback	Motor	Body movement + Keyboard	3D	Single Multi	None	Movement Simulation	No	Yes	Yes	Home

Chapter 6

Goniometer Tool Simulation

In this chapter, it is proposed the methodology and the following results for the development of an application for measuring range of shoulder and elbow motion using input data from Microsoft Kinect sensor. Furthermore, the results are compared against the data acquired with a clinical "gold standard" goniometer: an instrument for the precise measurement of angles (see Figure 6.1).

One of the most important factors for assessing body mobility is ROM, which are often evaluate using a universal goniometer in a clinical setting. Also, a patient cannot measure ROM using the universal goniometer without the assistance of a trained examiner. An approach to measure ROM without the assistance of a trained examiner is the key to both make measuring ROM at home feasible and to support the monitorization of a patient's physical rehabilitation. Another major factor for developing this application is to study the accuracy in VR systems where, accurate shoulder angle measurements are needed, for instance applications for breast cancer rehabilitation. In fact, accurate shoulder angle measurements are required for most musculoskeletal and neurological rehabilitation protocols [94].

In this study, it is hypothesized that the Microsoft Kinect can be used to measure the shoulder and elbow ROM by comparing data from the shoulder ROM acquired both from the Kinect sensor and from a universal goniometer, under optimal conditions. In case this method proves reliable, the aim is to apply this application in a clinical environment thus, it is imperative to develop a simple and intuitive interface for the user and robust to data loss.



Figure 6.1: Goniometer used in this study

6.1 Interface for goniometer tool simulation

The interface for this application was developed using the game engine Unity. The main reasons that led to this choice were the robustness to data loss and the capacity to develop easy-to-understand and fluid interfaces. The application interface consists of the following features:

- **Main menu**

The main menu principal function is to input the name or code of the patient, in order to provide a proper identification of the save information (see Figure 6.2).

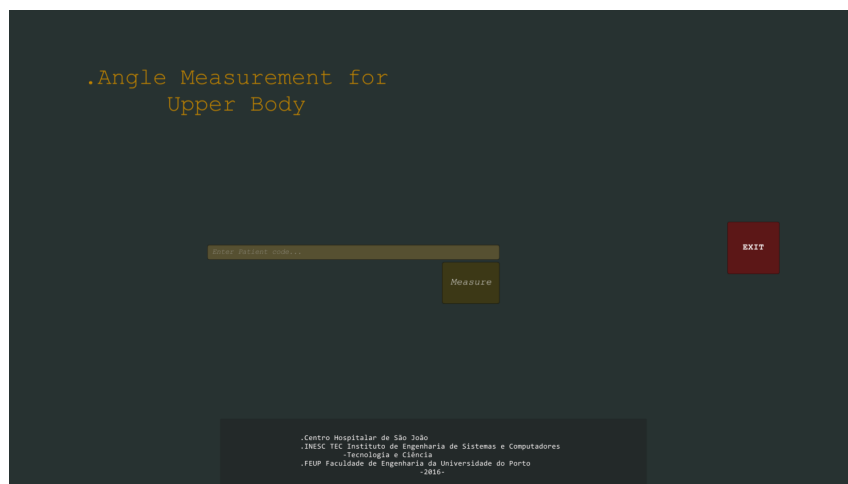


Figure 6.2: Goniometer simulation tool: Main menu

- **Measurement options**

Option to choose and save what angle to measure, in the acquisition environment it is possible to choose what angle to measure by click the respective button and, save its value by clicking in the button <Save measurement> (see Figure 6.3).

- **Operator options**

A set of components were add to favour a more easy and controlled acquisition are illustrated in Figure 6.3. For instance, the positions that are being tracked next to the color projection of the user, its possible to evaluate if the position is being done and tracked correctly.

- **Recording options**

The data is saved when the button <Save measurement> is pressed, acquiring a screenshot, a RGB and depth image, and a .csv file (with the value of the angle and its respective 20 skeleton joints).

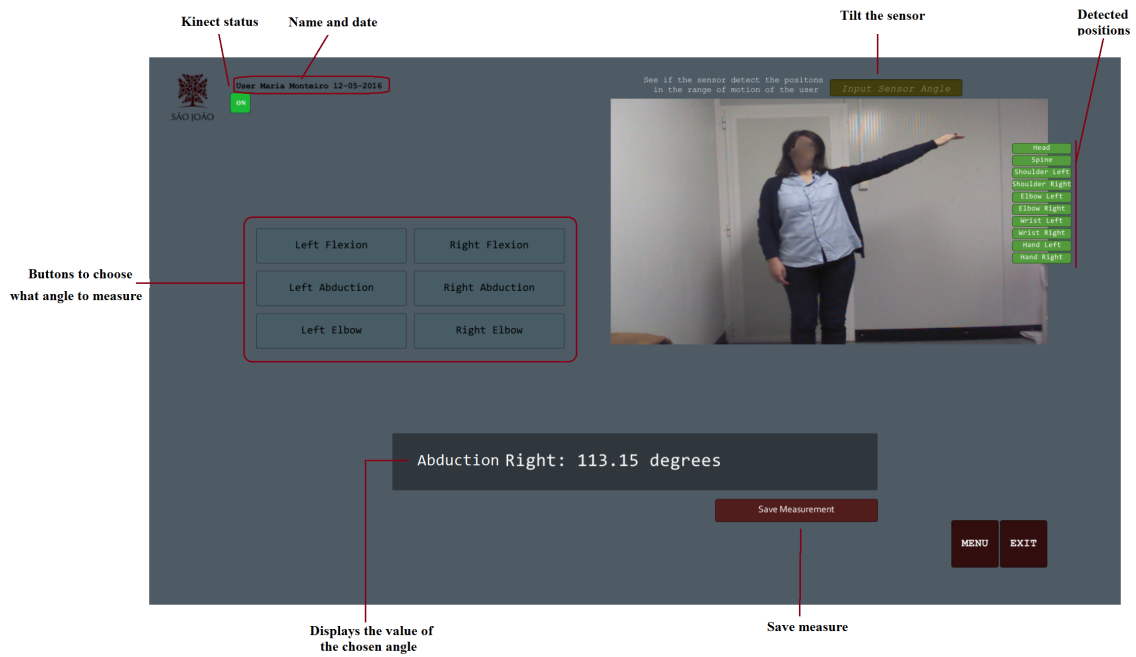


Figure 6.3: Goniometer simulation tool: Interface of the acquisition environment

6.1.1 Angles computation

The angles selected to be measure with this application were: shoulder flexion, shoulder abduction and elbow flexion. The reasons for this selection were the following: this set of angles is required in order to assess the exercises preformed in Chapter 5 and, the skeleton joints do not obstruct the view of the sensor for this poses.

The positions of shoulder and elbow joints relative to the trunk were used to measure the angles of shoulder flexion and abduction (in degrees), while the positions of the elbow and hand relative to the shoulder were used to measure the angle of elbow flexion (see Figure 6.4). The process to calculate this angles are displayed in a set of generalized equations in Equation 6.1 throw Equation 6.7.

i. Calculate the vectors from the skeleton points (p_1, p_2, p_3) :

$$v1 = \begin{pmatrix} p_{1x} \\ p_{1y} \\ p_{1z} \end{pmatrix} - \begin{pmatrix} p_{2x} \\ p_{2y} \\ p_{2z} \end{pmatrix} \quad (6.1)$$

$$v2 = \begin{pmatrix} p_{1x} \\ p_{1y} \\ p_{1z} \end{pmatrix} - \begin{pmatrix} p_{3x} \\ p_{3y} \\ p_{3z} \end{pmatrix} \quad (6.2)$$

ii. Normalize the vectors (v_1, v_2) :

$$|v_1| = \sqrt{v_1x^2 + v_1y^2 + v_1z^2} \quad (6.3)$$

$$|v_2| = \sqrt{v_2x^2 + v_2y^2 + v_2z^2} \quad (6.4)$$

$$\hat{v}_1 = \frac{v_1}{|v_1|} \quad (6.5)$$

$$\hat{v}_2 = \frac{v_2}{|v_2|} \quad (6.6)$$

iii. Calculate the dot product and convert to degrees:

$$Angle(degrees) = \frac{\arccos \hat{v}_1 \cdot \hat{v}_2}{\pi} \times 180 \quad (6.7)$$

6.2 Protocol used for acquisition

6.2.1 Methods

The goniometer used in this study has a scale of 5° with an error of $\pm 2.5^\circ$ and a range between 0° and 180° . It was provided by the Hospital de S. João with the aim of comparing the purpose method with a instrument commonly used in a clinical setting.

This study was conducted by setting the sensor in frontal and sagittal view. For frontal view, each participant held the following static poses (see Table 6.1): shoulder abduction, abduction to 90° and elbow flexion. The sagittal view poses were latter added, as pilot work revealed that the shoulder joint were occluded from the sensor in the frontal view during the flexion pose. The abduction to 90° and flexion to 90° was set using the goniometer, for the rest of the measures the participants were instructed to rotate whatever they choose. Once the pose was set, measurements were recorded simultaneously using the Microsoft Kinect and a goniometer.

Table 6.1: Goniometer simulation tool: Postures for acquisition data

	Front pose	Sagittal pose	Right side	Left side
Elbow rotation	x		x	x
Shoulder abduction	x		x	x
Shoulder flexion		x	x	
Flexion to 90°		x	x	
Abduction to 90°	x		x	

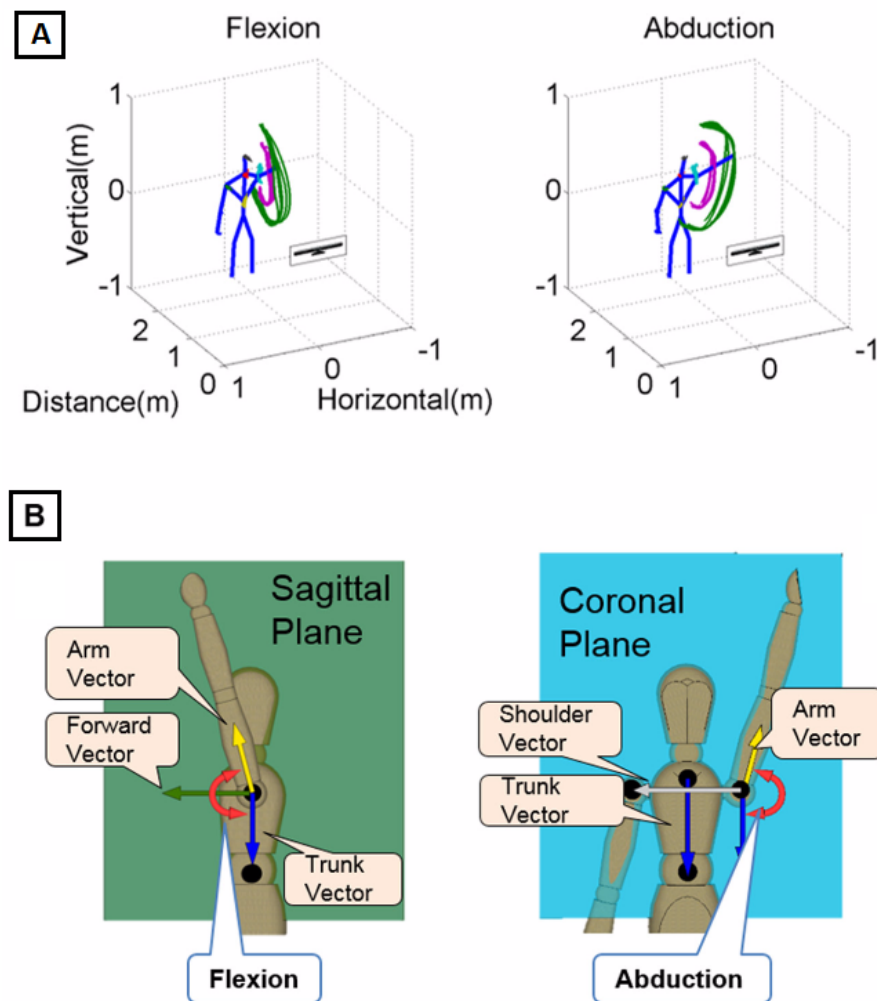


Figure 6.4: **A:** For each shoulder motion the body segments are traced. Green line is the trace of the left wrist and pink line is the trace of the left elbow. **B:** Calculation of the shoulder ROM angles by the projected angles on the defined anatomical planes, (From [95])

6.2.2 Participants

To maintain each pose for a significant period of time (stabilize the position and performing the measure with the goniometer) convenience samples of 10 and 7 asymptomatic adults with no known shoulder pathology participated in this study (Table 6.2).

Table 6.2: Brief summary of the test samples

Acquisition	Sample size	Female	Male	Age		Height		Weight	
				M	SD	M	SD	M	SD
Front pose	10	1	9	27.60	5.44	176 cm	0.06	72.50 kg	10.51
Sagittal pose	7	1	6	27.50	4.64	175 cm	0.08	70.21 kg	13.38

6.3 Experimental results

For the validation of this study, the application was programmed to save every frame of the procedure. The angle obtain for each measure was the result sequence average acquired from the moment a pose is stabilized until the measure with goniometer is performed (see Figure 6.5).

In this section, the results obtained are presented and discussed given the methodology introduce in the section above. The measurements are presented for each subject with the goniometer value and absolute error and, the application mean and standard deviation of the sequence used.

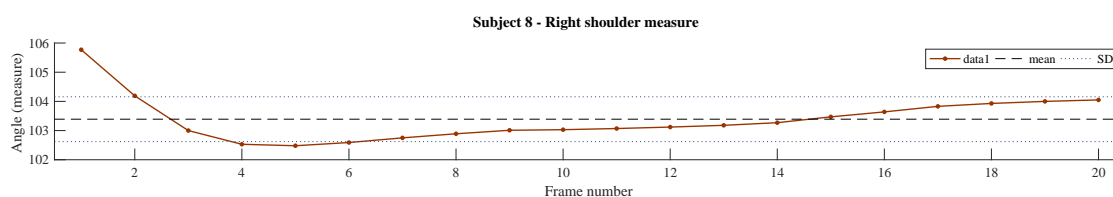


Figure 6.5: Subject ID=8, right shoulder sequence acquired

6.3.1 Shoulder abduction

In frontal pose, for each subject the shoulder abduction were recorded for the pose with an arbitrary abduction movement and, the pose with abduction at 90° measured set beforehand using the goniometer. As illustrated in Figure 6.6, the measures performed with the application never surpass the error of the goniometer. The standard deviation of the sequence varies from subject to subject (see Table 6.3), this reflects the sensitivity of the sensor to any fluctuation of movement.

Table 6.3: Shoulder measures (in degrees)

Pose	Subject ID	Microsoft Kinect				Goniometer	
		Right side		Left side		Right side	Left side
		Mean	SD	Mean	SD	Measure	
Shoulder abduction	1	141.80	0.19	159.50	0.41	140.00±2.5	157.50±2.5
	2	131.63	0.64	131.31	0.52	130.00±2.5	130.00±2.5
	3	158.66	2.67	145.27	1.61	160.00±2.5	145.00±2.5
	4	121.71	1.29	141.84	0.47	122.50±2.5	140.00±2.5
	5	130.99	1.24	147.10	0.37	130.00±2.5	147.50±2.5
	6	130.34	0.46	141.01	0.52	130.00±2.5	140.00±2.5
	7	130.55	1.088	140.57	1.40	130.00±2.5	140.00±2.5
	8	103.39	0.77	135.61	0.42	105.00±2.5	135.00±2.5
	9	115.15	0.31	149.97	0.35	115.00±2.5	150.00±2.5
	10	101.22	1.00	130.26	0.75	100.00±2.5	130.00±2.5

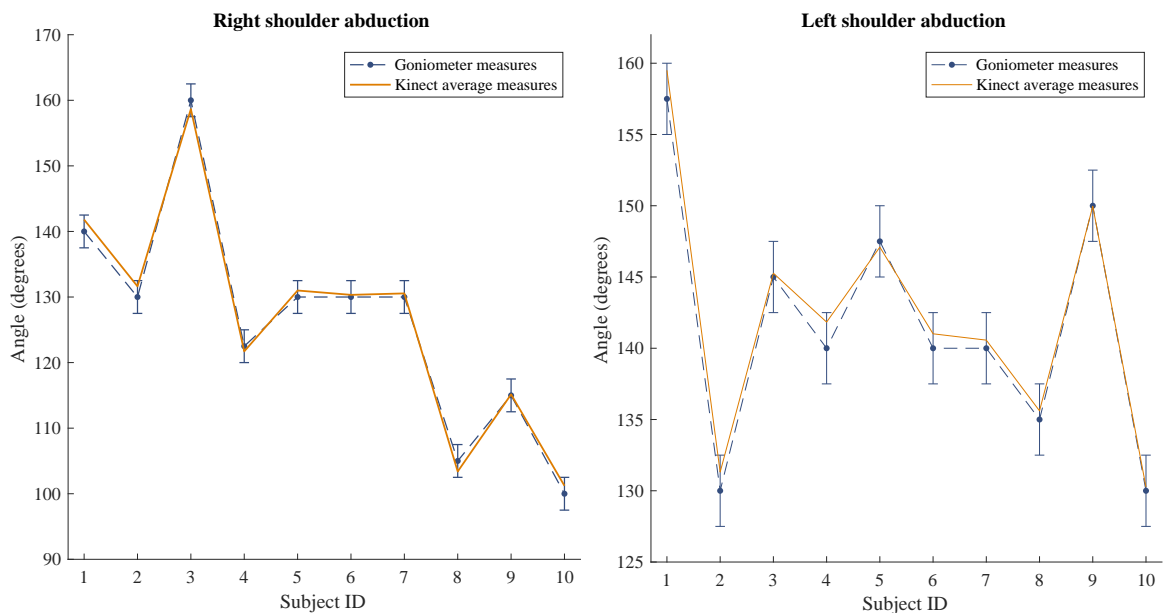


Figure 6.6: Shoulder measures

When the right shoulder abduction is set at 90° prior with the goniometer, for every test subject the measure with application does not exceed the one with the goniometer (see Figure 6.7). The sequence used for the sensor angle has a SD maximum of 0.72 for subject 1 and, a minimum for subject 10 with 0.09 (see Table 6.4).

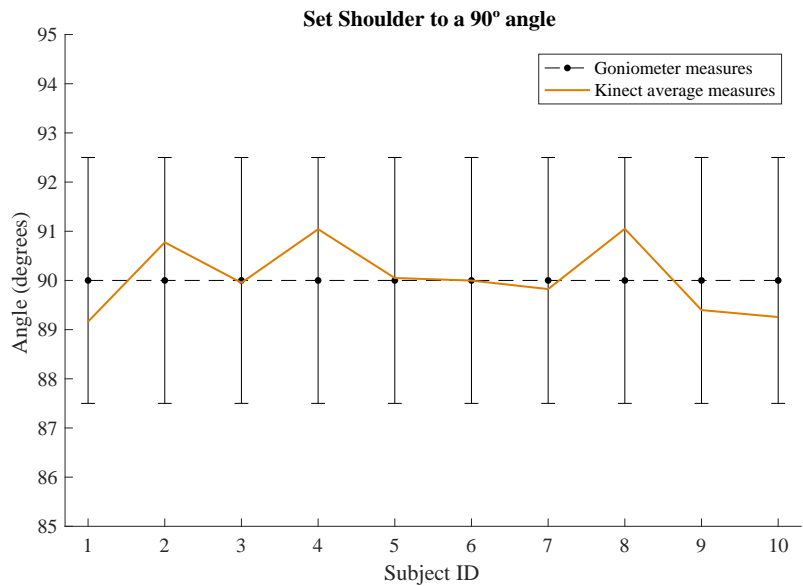


Figure 6.7: Shoulder angle set to 90°

Table 6.4: Set shoulder to 90°

Pose	Subject ID	Microsoft Kinect		Goniometer
		Right side		Right side
		Mean	SD	Measure
Set shoulder to 90°	1	89.16	0.72	90.00±2.5
	2	90.77	0.19	90.00±2.5
	3	89.95	0.46	90.00±2.5
	4	91.04	0.43	90.00±2.5
	5	90.05	0.53	90.00±2.5
	6	90.00	0.48	90.00±2.5
	7	89.82	0.45	90.00±2.5
	8	91.05	0.84	90.00±2.5
	9	89.40	0.58	90.00±2.5
	10	89.26	0.09	90.00±2.5

6.3.2 Elbow rotation

The elbow rotation was performed in the frontal pose, with the arm to the side so sensor did not have its view obstructed. For each subject was asked to perform a random elbow rotation, the results are in agreement with both measures for all the subjects (see Figure 6.8 and Table 6.5).

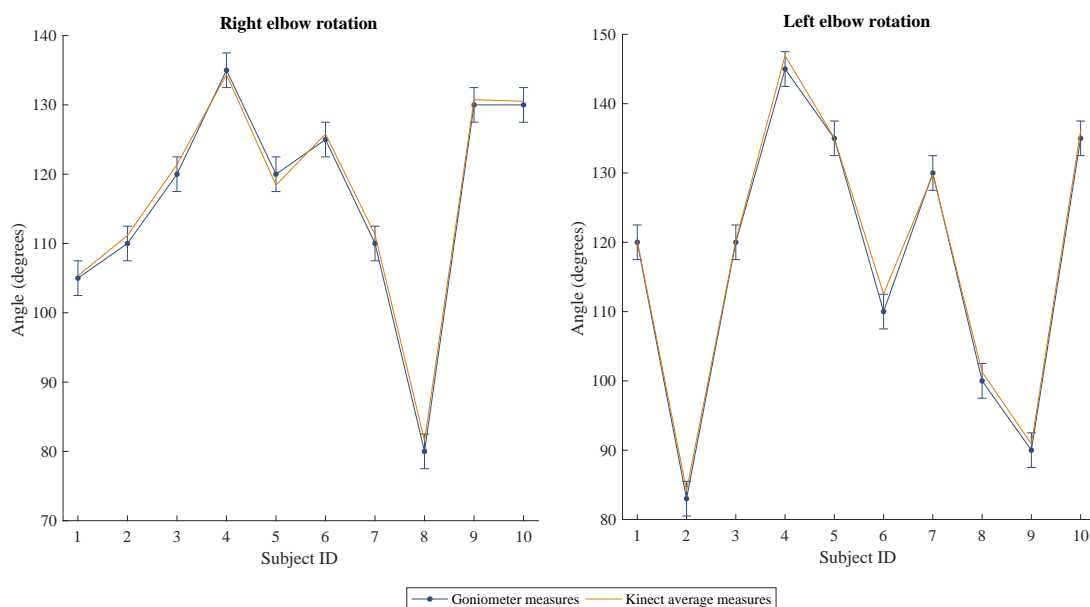


Figure 6.8: Elbow measures

Table 6.5: Elbow rotation measures (in degrees)

Pose	Subject ID	Microsoft Kinect				Goniometer	
		Right side		Left side		Right side	Left side
		Mean	SD	Mean	SD	Measure	
Elbow flexion	1	105.36	0.32	120.20	1.06	105.00±2.5	120.00±2.5
	2	111.15	0.27	84.19	0.17	110.00±2.5	83.00±2.5
	3	121.40	0.46	120.24	0.35	120.00±2.5	120.00±2.5
	4	134.38	0.91	146.94	2.58	135.50±2.5	145.00±2.5
	5	118.42	0.99	135.04	0.26	120.00±2.5	135.50±2.5
	6	125.81	0.38	112.56	0.69	125.00±2.5	110.00±2.5
	7	111.29	0.82	129.73	1.36	110.00±2.5	130.00±2.5
	8	81.54	2.00	101.28	0.34	80.00±2.5	100.00±2.5
	9	130.75	1.73	90.90	0.91	130.00±2.5	90.00±2.5
	10	130.52	1.74	136.11	0.64	130.00±2.5	135.00±2.5

6.3.3 Shoulder flexion

The shoulder flexion was recorded in sagittal pose, with each subject asked to choose and maintain a flexion movement and, then to hold the shoulder flexion at 90° measured prior with goniometer. For both poses the results were in conformity with the goniometer results, with neither subject measure exceeding the goniometer error (see Figure 6.9 and Figure 6.10). The SD for the selected sequence, for poses with random shoulder flexion has a maximum of 0.85 for subject 2 and, a minimum of 0.10 for subject 6 (see Table 6.6).

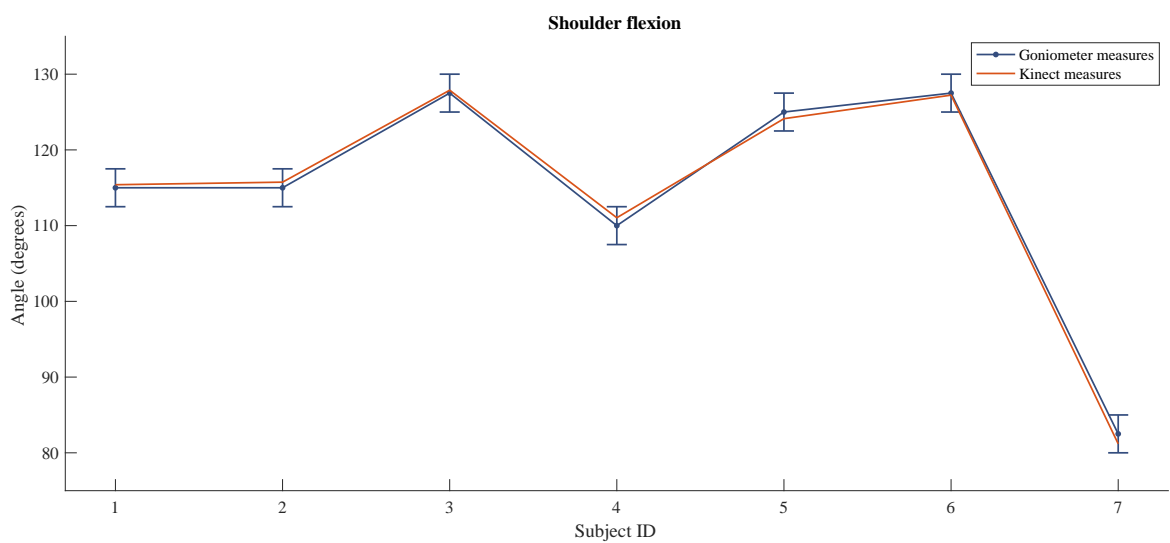


Figure 6.9: Shoulder flexion

Table 6.6: Shoulder flexion in sagittal pose

Pose	Subject ID	Microsoft Kinect Right side		Goniometer Right side
		Mean	SD	Measure
Shoulder flexion	1	115.40	0.46	115.00±2.5
	2	115.74	0.85	115.00±2.5
	3	127.90	0.70	127.50±2.5
	4	111.04	0.54	110.00±2.5
	5	124.12	0.51	125.00±2.5
	6	127.23	0.10	127.50±2.5
	7	81.19	1.15	82.5±2.5

For shoulder flexion set at 90° in sagittal pose, the SD for the selected sequence has its maximum at 1.12 for subject 1 and, the minimum for subject 3 with 0.09 (see Table 6.7).

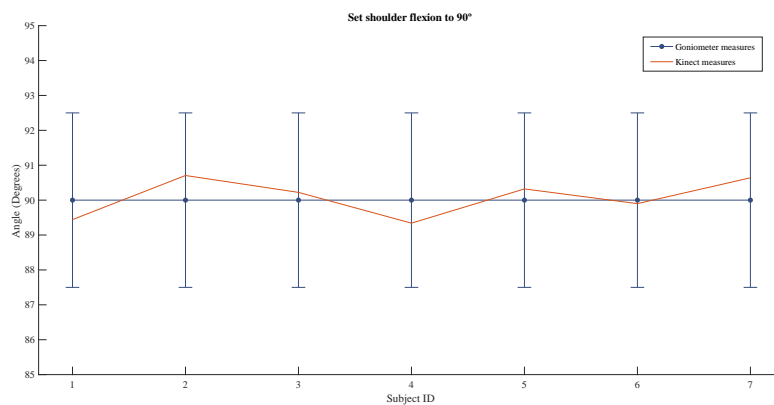


Figure 6.10: Shoulder flexion to 90°

Table 6.7: Set shoulder flexion to 90° in sagittal pose

Pose	Subject ID	Microsoft Kinect Right side		Goniometer Right side
		Mean	SD	Measure
Flexion shoulder to 90°	1	89.44	1.12	90.00±2.5
	2	90.70	0.28	90.00±2.5
	3	90.22	0.09	90.00±2.5
	4	89.34	0.79	90.00±2.5
	5	90.32	0.35	90.00±2.5
	6	89.90	0.90	90.00±2.5
	7	90.64	0.23	90.00±2.5

6.4 Summary

The Microsoft Kinect is an easy-to-use and non-intrusive device, which makes the sensor a good contender to assess elbow and shoulder ROM in a clinical or home setting.

This study showed that the average difference for each measure performed with the proposed application never surpasses the goniometer error (see Table 6.8), which leads to consider the Microsoft Kinect a reliable method to measure shoulder and elbow ROM based on its agreement with the goniometric measurements. Nevertheless, more tests should be performed before stating with certainty that the proposed application can be used without any trepidation in a clinic or home base setting. For this purpose, the following research is suggested:

- Test a set of poses with more than one examiner, given the fact that for the same posture the measure performed may vary between examiners;

- To validate the usefulness of the proposed application, it is necessary to perform tests in a clinical setting with subjects of different backgrounds and physical condition, in order to attain, in this particular setting, its limitations and level of usefulness. This is a very important aspect to assess because in this study were clear the variation between subjects when the position is maintained for a short period of time.

In conclusion, this study revealed the application was reliable when compared with the results from the goniometer. Based on this results it is possible to assumed that the skeletal data from the Microsoft Kinect to be reliable for the measurement of shoulder and elbow angle in the selected poses. Nevertheless, it is imperative to emphasize that this assumption is made one the basis of an indirect measure.

Table 6.8: General results (in degrees)

Pose	Measure	Average difference
		Absolute value
Front	Right shoulder abduction	0.29°
Front	Left shoulder abduction	0.74°
Front	Right elbow rotation	0.44°
Front	Left elbow rotation	1.17°
Front	Set shoulder to 90°	0.05°
Sagittal	Shoulder flexion	0.71°
Sagittal	Set shoulder to 90°	0.45°

Chapter 7

Recognizing Human Activity Using RGB-D Data

For the past several decades, human action recognition has been an active area of research due to its applications in areas such as surveillance, video games and robotics. With several approaches proposed for recognizing human actions from monocular RGB video sequences. Unfortunately, the monocular RGB data is highly sensitive to various factors such as variations in view-point and illumination, occlusions and background clutter. Moreover, monocular video sensors do not capture in its entirety the human motion in 3D space [96].

The recent fruition of cost effective depth sensors, extracting the human skeleton has become a task relatively easier to attain. These sensors provide 3D depth data of the scene which offers useful information to recover 3D human skeletons, where illuminations changes cease to be a problem. Of late, *Shotton et al.* [97] proposed a method to accurately and promptly estimate the 3D positions of skeletal joints using a single depth image. These recent advances have resulted in a renewed interest in skeleton-based human action recognition.

Skeleton-based action recognition approaches can be broadly grouped into two main categories [98]:

- **Joint-based approaches:** Regard the human skeleton simply as a set of points. These approaches try to model the motion of either individual joints or combinations of joints using various features such joint positions, joint orientations a fixed coordinate axis, pairwise relative joint positions, among others.

- **Body part-based approaches:** Consider the human skeleton as a connected set of rigid segments (body parts). These approaches either model the temporal evolution of individual body parts or focus on (directly) connected pairs of body parts and model the temporal evolution of joint angles.

Previous, it was highlighted the necessity of a method that recognizes accurately the actions performed by the users when performing the exercises, with the main objective to assist the monitoring process of the players progress. In this chapter, it is present the starting point of a study in action recognition in order to achieve the stated objective.

7.1 Machine learning overview

Machine learning (ML) is a subfield of computer science that evolved from the study of pattern recognition and the computational learning theory in artificial intelligence. In 1959, Arthur Samuel defined ML as a *"field of study that gives computers the ability to learn without being explicitly programmed"*. ML algorithms iteratively learn from data by generalizing their experience into models [99]. This is often feasible and cost-effective where manual programming is not. As more data becomes available, more ambitious problems can be tackled.

Several types of ML exist for the problem of human action recognition the focus will be directed to classification. A classifier is a system that inputs (typically) a vector of discrete and/or continuous feature values and outputs a single discrete value, the class. This systems have two main components (see Figure 7.1):

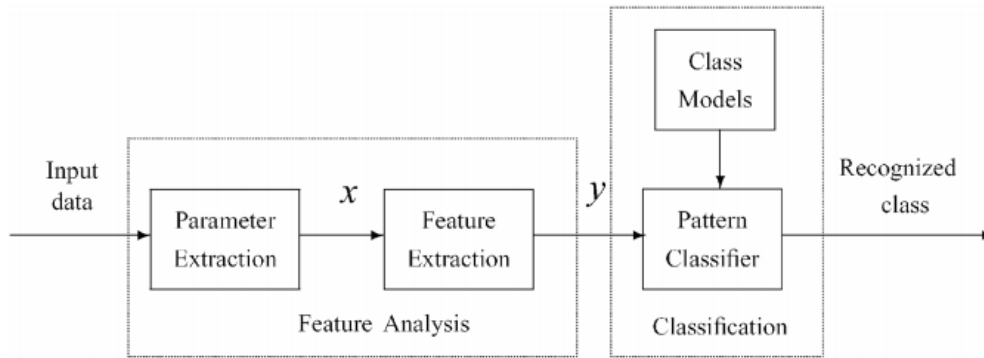


Figure 7.1: Conventional pattern recognition system, (From [100])

- Feature analysis, it is achieved in two steps: parameter extraction step and feature extraction step. In the parameter extraction step, information relevant for pattern classification is extracted from the input data in the form of a p -dimensional parameter vector x . Then, in feature extraction the parameter vector X is transformed to y with dimensionality m ($m \leq p$).
- Classification, the trained classifier assigns the new observation y to a class.

For example, a spam filter classifies email messages into “spam” or “not spam,” and its input may be a Boolean vector $x = (x_1, \dots, x_j, \dots, x_d)$, where $x_j = 1$ if the j^{th} word in the dictionary appears in the email and $x_j = 0$ otherwise. To a learner is input a training set of examples (x_i, y_i) , where $x_i = (x_{i,1}, \dots, x_{i,d})$ is an observed input and y_i is the corresponding output, and outputs a classifier. The test of the learner is whether this classifier produces the correct output y_i for future examples x_i (e.g., whether the spam filter correctly classifies previously unseen emails as spam or not spam).

Assuming there is a problem in the develop of an application and ML techniques can be a possible solution, the first problem that arises is which one to use. Because of the bewildering variety

of learning algorithms available it is necessary to narrow its focus in the following points [101]:

Representation. A classifier must be represented in some formal language that the computer can handle. Selecting a representation for a learner is equivalent to choosing the set of classifiers that it can possibly learn. This set is called the hypothesis space of the learner. If a classifier is not in the hypothesis space, it cannot be learned. A related question, is how to represent the input, i.e., what features to use.

Evaluation. An evaluation function (also called objective/scoring function) is required to distinguish which ones are good classifiers. The evaluation function used internally by the algorithm may differ from the external one that we want the classifier to optimize, for ease of optimization (see Table 7.1).

Optimization. Lastly, its necessary a method to search among the classifiers in the language for the highest-scoring one. The choice of optimization technique is key to the efficiency of the learner, and also helps determine the classifier produced if the evaluation function has more than one optimum. Usually, new learners start out using off-the-shelf optimizers, which are later replaced by custom-designed ones.

Common examples for each of these three components are shown in Table 7.1. For example, k -nearest neighbour (k NN) classifies a test example by finding the k most similar training examples and predicting the majority class among them. Hyperplane based methods such as support vector machines (SVM) form a linear combination of the features per class and predict the class with the highest-valued combination, further on some of these methods will be discussed in more detail.

Table 7.1: The three components of learning algorithms, (Adapted from [101])

Representation	Evaluation	Optimization
Instances:	Accuracy/Error rate	Combinatorial optimization:
- k -nearest neighbor	Precision and recall	- Greedysearch
- Support vector machines	Squared error	- Beam search
Hyperplanes:	Likelihood	- Branch-and-bound
- Naive Bayes Posterior	Posterior probability	Continuous optimization:
- Logistic regression	Information gain	- Unconstrained:
Decision trees	K-L divergence	.Gradient descent
Sets of rules:	Cost/Utility	.Conjugate gradient
- Propositional rules	Margin	.Quasi-Newton methods
- Logic programs		- Constrained:
Neural networks		.Linear programming
Graphical models:		.Quadratic programming
- Bayesian networks		
- Conditional random fields		

7.1.1 k -Nearest Neighbour

This subsection presents an overview of k NN perhaps the most straightforward classifier from all the available ML techniques. Nearest neighbour (NN) classification is achieved by identifying the NN to a query example and using those neighbours to determine the class of the query. The basic idea is as shown in Figure 7.1 which depicts a 3-NN Classifier on a two-class problem in a two-dimensional feature space. In this example the decision for q_1 is straightforward – all three of its nearest neighbours are of class O so it is classified as an O . The situation for q_2 is a bit more complicated as it has two neighbours of class X and one of class O . This can be resolved by simple majority voting or by distance weighted voting. Thus KNN classification has two stages; the first is the determination of the NN following the selection of the class using those neighbours [102].

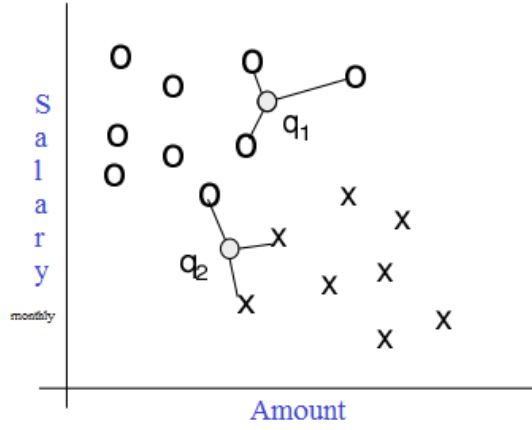


Figure 7.2: A simple example of 3-Nearest Neighbour Classification, (From [102])

Now, hypothesize a training dataset D made of $(x_i)_{i \in [1, |D|]}$ training samples. The examples are described by a set of features F and any numeric features have been normalised to the range $[0, 1]$. Each training example is labelled with a class label $y_j \in Y$. The objective is to classify an unknown example q .

$$d(q, x_i) = \sum_{f \in F} w_f \delta(q_f, x_{if}) \quad (7.1)$$

For the distance metric there are a large range of possibilities; a simplified version for continuous and discrete attributes would be:

$$\delta(q_f, x_{if}) = \begin{cases} 0 & f \text{ discrete and } q_f = x_{if} \\ 1 & f \text{ discrete and } q_f \neq x_{if} \\ |q_f - x_{if}| & f \text{ continuous} \end{cases} \quad (7.2)$$

The k nearest neighbours are selected based on this distance metric. Then there are a variety of ways in which the k NN can be used to determine the class of q . The most direct approach is to assign the majority class among the nearest neighbours to the query. It will often make sense to assign more weight to the nearer neighbours in deciding the class of the query. A fairly general technique to achieve this is distance weighted voting where the neighbours get to vote on the class of the query case with votes weighted by the inverse of their distance to the query.

$$\text{Vote}(y_i) = \sum_{c=1}^k \frac{1}{d(q, x_c)^n} 1(y_j, y_c) \quad (7.3)$$

Thus the vote assigned to class y_j by neighbour x_c is 1 divided by the distance to that neighbour, i.e. $1(y_j, y_c)$ returns 1 if the class labels match and 0 otherwise. In equation 7.3, n would normally be 1 but values greater than 1 can be used to further reduce the influence of more distant neighbours.

7.1.2 Support Vector Machines

The SVM was first proposed by *Vapnik* [103] and has since attracted a high degree of interest in the ML research community. This supervised learning model has been used in a wide net of real world problems such as text categorization, tone recognition, image classification and object detection, hand-written digit recognition, micro-array gene expression data analysis and data classification [104].

SVMs are based on the concept of decision plans that define decision limits, that separates all the points of one class from another and classifies the data according to the hyperplane. The best hyperplane (see Figure 7.3) for the SVM is one that allows a greater margin between the two classes. Support vectors are the data points that are closer to the hyperplane that separates the classes and which are situated at the edge of the margin [105].

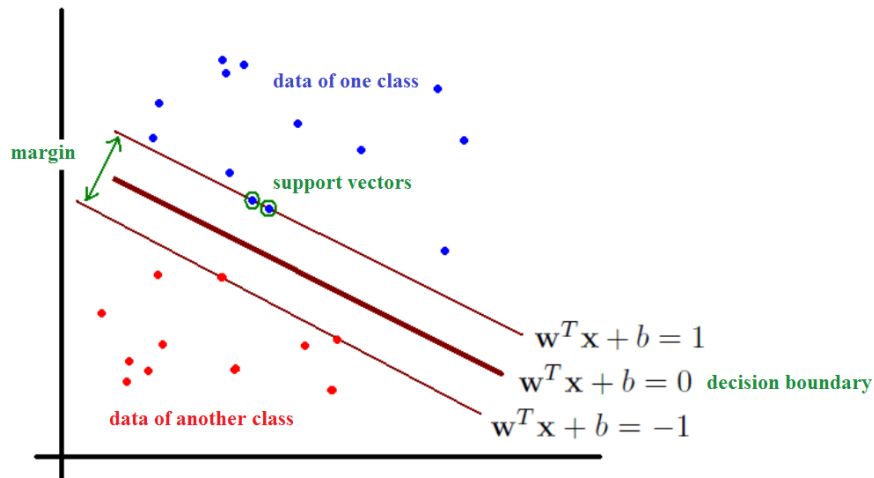


Figure 7.3: Linear separating hyperplanes for the separable case, the support vectors are circled, (Adapted from [106])

In a number of cases, it has been proven that SVM is consistently superior compare to other supervised learning methods. However, for some datasets, the performance of SVM is very sensitive to how the cost parameter and kernel parameters are set (see Figure 7.4). As a result, extensive cross validation has to be performed in order to figure out the optimal parameter setting, commonly referred as model selection. One practical issue with model selection is that this process is very time consuming. A number of parameters associated with the use of the SVM algorithm that can impact the results [104], these parameters include:

- Choice of kernel functions;
- Standard deviation of the Gaussian kernel;
- Relative weights associated with slack variables to account for the non-uniform distribution of labeled data;
- Number of training examples.

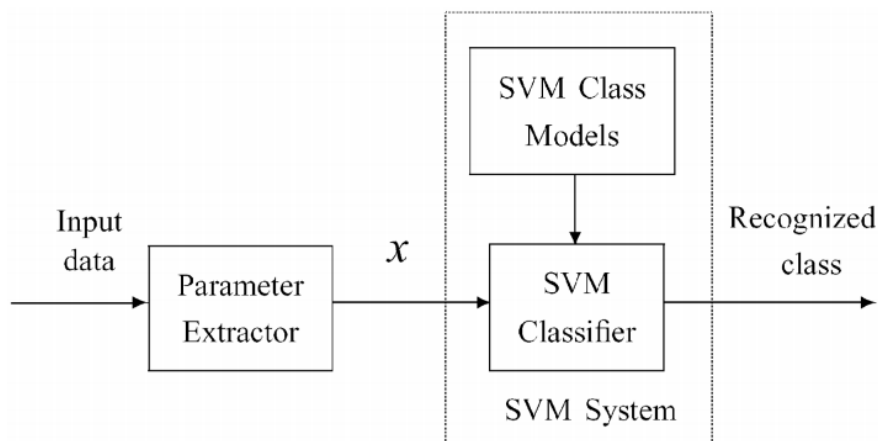


Figure 7.4: SVM recognition system, (From [100])

When classes are not linearly separable in the feature space it is no longer possible find a hyperplane that allows to perfectly separate the points of the two classes. In this case, a smooth margin is used in the SVM, that is, a hyperplane that separates many, but not all the data points. The goal is to make as large a margin as possible and at the same time, decrease the number of badly ranked points as much as possible. In this way, arises the need to control the two objectives:

- Maximize margin
- Minimize the number of wrong ratings

Linear SVMs are effective in classifying linearly separable datasets or that have an approximately linear distribution, and the soft-margin version tolerates the presence of some noise and wrong sorting. However, there are many cases in which it is possible to satisfactorily divide the training data by a hyperplane (see Figure 7.5).

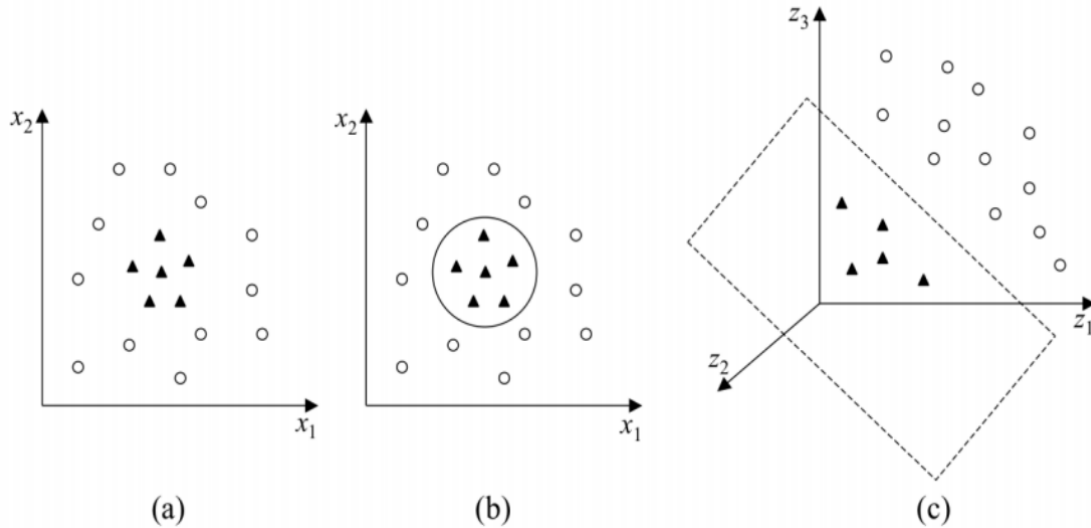


Figure 7.5: (A) Nonlinear data set; (B) Non-linear boundary in the input space; (w) Linear boundary in the space of features, (From [105])

SVMs deal with non-linear problems mapping the training set of their original space, space of the entrances, to a new space of greater dimension, called space of the characteristics. Therefore, the data is initially mapped to a larger space and applies The SVM linear over this space, thus allowing to find the hyperplane with greater margin of separation.

However, the space of the features may be very large and computing of the mapping can be quite time consuming and costly. Fortunately, the SVM methodology has a elegant property that allows the mapping implicit in large spaces. This method is based on the idea that once a hyperplane has been created, the kernel function is used to map new points into the feature space for classification [107]. The selection of an appropriate kernel function is important, since the kernel function defines the transformed feature space in which the training set instances will be classified.

7.1.2.1 Multi-class SVM classifiers

SVM is a two-class based pattern classification algorithm, in order to extend this method for a multi-class based classifier exist the two following approaches (it is unknown which method the best) [108]:

- “One vs. all” type classifier proposed by *Scholkopf et al.* [109], this approach builds for each class a classifier which separates all classes from each other (Figure 7.6 (a)). For instance, x

is then classified as belonging to the class whose boundary maximizes $(w \cdot x) + b$.

- “One vs. one” type classifier proposed by *Clarkson and Moreno* [108], this approach simply constructs for each pair of classes a classifier which separates those classes (Figure 7.6 (b)). A test example is then classified by all of the classifiers, and is said to belong to the class with the largest number of positive outputs from these sub-classifiers.

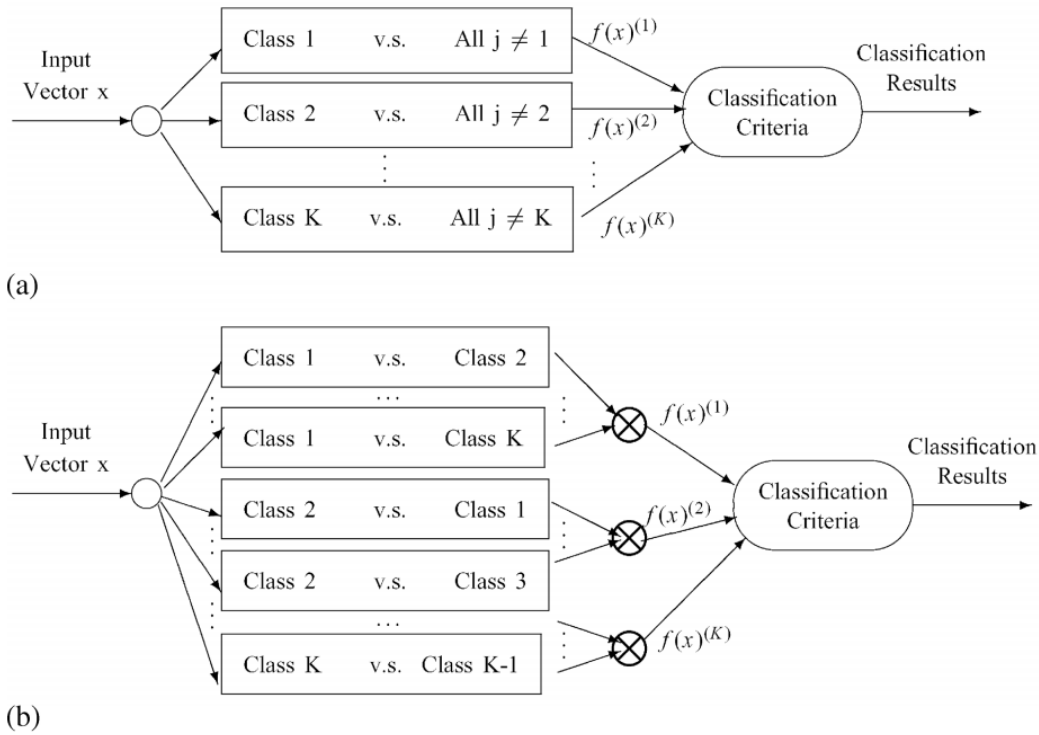


Figure 7.6: Two types of multi-class SVM classifier: (a) Structure of “one vs. all” multi-class SVM Classifier; (b) Structure of “one vs. one” multi-class SVM classifier, (From [100])

7.1.3 Summary: Advantages and Disadvantages of available classifiers

In resume, no single learning algorithm can uniformly outperform other algorithms over all datasets. Features of learning techniques are compared in Table 7.2 (from evidence of existing empirical and theoretical studies). An overview of the advantages and disadvantages follows for the methods prior analysed. The kNN classifier should be considered in seeking a solution to any classification problem given its interpretability and simple implementation, the follow advantages and

disadvantages derive from this attributes [102]:

- Easy to implement and debug because the process is transparent;
- When an explanation of the classifier output is helpful, k NN can be very effective if an analysis of the neighbours is useful as a visual explanation;
- Improving the accuracy of the classifier can be accomplished by some noise reduction techniques that work only for k NN;
- Case-Retrieval Nets are an elaboration of the Memory-Based Classifier idea that can greatly improve run-time performance on large case-bases;
- k NN can have poor runtime performance if the training set is large because all the work is done at runtime;
- k NN is very sensitive to irrelevant or redundant features because all features contribute to the similarity and thus to the classification. This can be ameliorated by careful feature selection or feature weighting.

In case of very difficult classification tasks, k NN may be outperformed by more exotic techniques such as SVMs or Neural Networks. The most notable advantages and disadvantages for the SVM classifiers are the following:

- Less overfitting;
- Robust to noise;
- SVM is a binary classifier. To do a multi-class classification, pair-wise classification can be used (one class against all others, for all classes);
- SVMs are robust in the face of large data;
- The use of Kernel functions in the non-linearization of SVMs makes the algorithm efficient, since it allows the construction of simple hyperplanes in a space of high dimension in a computationally treatable way ;
- SVMs sensitivity to choices of parameter values and the difficulty of interpretation of the model generated by this technique, problems that have been addressed in several recent works, as an example [110] and [111], respectively.

7.1.4 Dimension Reduction

Dimension reduction (or feature extraction algorithm) is a core research topic in the processing of multimedia data, it is a standard way of reducing intrinsic complexity of data with the purpose of facilitating its further analysis. In the process, certain characteristics of data are expected to be preserved. Particularly, for data with clustering structure is anticipated to be preserved as much as possible. Among more recent works, *Faivishevsky et al.* [112] proposes a method that preserves

Table 7.2: Comparing learning algorithms (***** stars represent the best and * star the worst performance), (Adapted from [107])

	Accuracy in general	Speed of learning	Speed of classification	Tolerance to missing values	Tolerance to irrelevant attributes	Tolerance to redundant attributes	Dealing with discrete/ binary/ continuous attributes	Tolerance to noise	Dealing with danger of overfitting	Attempts for incremental learning	Explanation ability/ transparency of knowledge/ classifications	Model parameter handling
Decision Trees	**	***	*****	****	****	**	*****	**	**	**	*****	***
Neural Networks	***	*	*****	*	*	**	*** (not discrete)	**	*	***	*	*
Naïve Bayes	*	*****	*****	****	**	*	*** (not continuous)	***	***	****	*****	*****
kNN	**	*****	*	*	**	**	*** (not directly discrete)	*	***	****	**	***
SVM	****	*	*****	**	*****	***	** (not discrete)	**	**	**	*	*
Rule learners	**	**	*****	**	**	**	*** (not directly continuous)	*	**	*	*****	***

clustering structure. An interesting overview of methods for feature extraction algorithms is done in [100].

As an example, in using k NN with high dimension data there are several reasons why it is useful to perform feature selection:

- For many distance measures, the retrieval time increases directly with the number of features;
- Noisy or irrelevant features can have the same influence on retrieval as predictive features so they will impact negatively on accuracy;
- Things look more similar on average the more features used to describe them (see Figure 7.7).

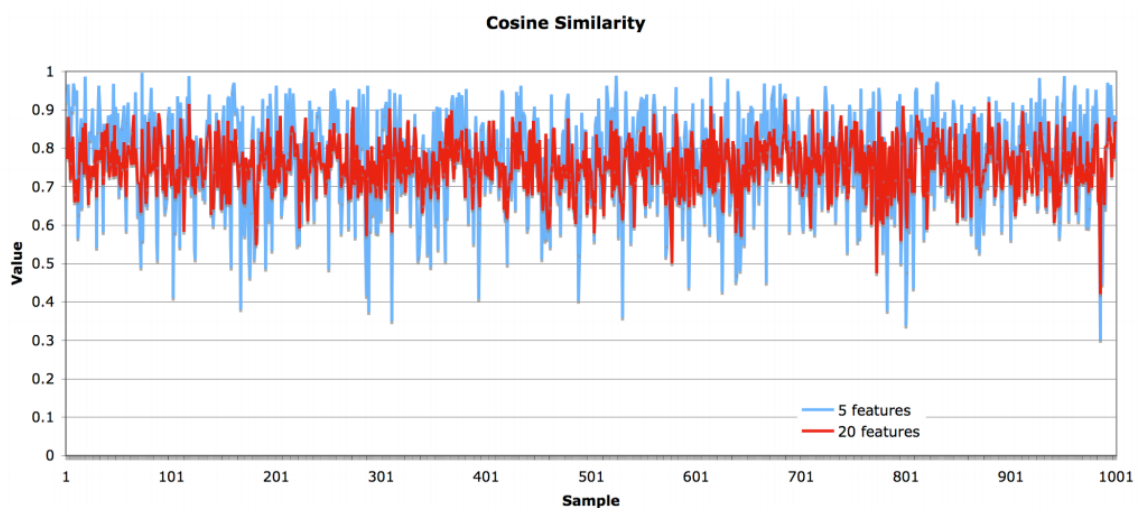


Figure 7.7: The more dimensions used to describe objects the more similar on average things appear. This figure shows the cosine similarity between objects described by 5 and 20 features. It is clear that in 20 dimensions similarity has a lower variance than in 5, (From [102])

Feature Selection techniques typically incorporate a search strategy for exploring the space of feature subsets, including methods for determining a suitable starting point and generating successive candidate subsets, and an evaluation criterion to rate and compare the candidates, which serves to guide the search process. The evaluation schemes can be divided into two broad categories:

Filter approaches. Attempt to remove irrelevant features from the feature set prior to the application of the learning algorithm. Initially, the data is analysed to identify those dimensions that are most relevant for describing its structure. The chosen feature subset is subsequently used to train the learning algorithm. Feedback regarding an algorithms performance is not required during the selection process, though it may be useful when attempting to gauge the effectiveness of the filter.

Wrapper methods. For feature selection make use of the learning algorithm itself to choose a set of relevant features. The wrapper conducts a search through the feature space, evaluating candidate feature subsets by estimating the predictive accuracy of the classifier built on that subset. The goal of the search is to find the subset that maximises this criterion.

7.1.5 Confusion Matrix

A confusion matrix is a technique used in ML for summarizing the performance of a classification algorithm. Classification accuracy alone can be misleading if there is an unequal number of observations in each class or if there are more than two classes in your dataset. Calculating a confusion matrix can be useful in the features selection because it is given a better idea of what the classification model is getting right and what types of errors it is making [113].

		Predicted Number			
		Class 1	Class 2	...	Class n
Actual Number	Class 1	x_{11}	x_{12}	...	x_{1n}
	Class 2	x_{21}	x_{22}	...	x_{2n}

	Class n	x_{n1}	x_{n2}	...	x_{nn}

Figure 7.8: A sample format of a confusion matrix with n -classes, (From [113])

The total numbers of false negative (TFN), false positive (TFP), and true negative (TTN) for each class i will be calculated based on the Generalized Equations 7.4, 7.5, and 7.6, respectively. The total true positive in the system its be obtained through Equation 7.7 and the overall accuracy in Equation 7.8.

$$TFN_i = \sum_{j=1, j \neq i}^n x_{ij} \quad (7.4)$$

$$TFP_i = \sum_{j=1, j \neq i}^n x_{ji} \quad (7.5)$$

$$TTN_i = \sum_{j=1, j \neq i}^n \sum_{k=1, k \neq i}^n x_{jk} \quad (7.6)$$

$$TTP_{all} = \sum_{j=1}^n x_{ij} \quad (7.7)$$

$$Overallaccuracy = \frac{TTP_{all}}{TotalNumberofTestingEntries} \quad (7.8)$$

In order to compute precision some the following statistical measures can be performed:

- Precision (P), is the fraction of retrieved instances that are relevant (see the generalized Equation 7.9, for each class i);
- Recall (R), measures the proportion of positives that are correctly identified as such (see the generalized Equation 7.10, for each class i);
- Specificity (S), measures the proportion of negatives that are correctly identified as such (see the generalized Equation 7.11, for each class i);
- F-score (F_1), it is a measure accuracy using both P and R to compute the score (see Equation 7.12).

$$P_i = \frac{TTP_{all}}{TTP_{all} + TFP_i} \quad (7.9)$$

$$R_i = \frac{TTP_{all}}{TTP_{all} + TFN_i} \quad (7.10)$$

$$S_i = \frac{TTP_{all}}{TTP_{all} + TFP_i} \quad (7.11)$$

$$F_1 = 2 \frac{P \cdot R}{P + R} \quad (7.12)$$

7.2 Activity Classification

Approaches for movement recognition can be grouped into the following categories [114]:

Space-time approaches. A video is depicted as a collection of feature points which are used for classification. This approach generally involves the detection and descriptors computation of interest points. The collection of these descriptors (bag-of-words) is therefore the representation of a video. The descriptors of labelled training data are presented to a classifier during training. Commonly used classifiers in the space-time approach to activity classification include SVM and

k NN, for example.

Sequential approaches. An activity is represented as an ordered sequence of features, whereas the goal is to learn the order of specific activity using state-space models. Hidden Markov Models (HMM) and other Dynamic Bayesian Networks (DBN) are popular state-space models used in activity recognition. If an activity is represented as a set of hidden states, each hidden state can produce a feature at each time frame, known as the observation.

Hierarchical approaches. The main idea is to perform recognition of higher-level activities by modelling them as a combination of other simpler activities. The major advantage of these approaches over sequential approaches is their ability to recognize activities with complex structures. In hierarchical approaches, multiple layers of state-based models such as HMMs and other DBNs are used to recognize higher level activities.

7.3 Methodology

The overall process of the proposed method is illustrated in Figure 7.9. It can be divided into three steps: feature extraction of the 3D skeletal joint location, label each action sequence and classification.

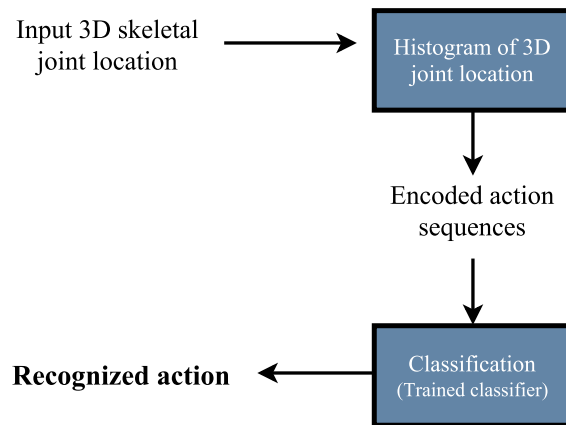


Figure 7.9: Overview of the implemented method for human action recognition

7.3.1 Feature Extraction

The proposed 3D skeletal joint feature is inspired on the work of *Xia et al.* [98]. This methodology is designed to be view invariant, meaning descriptors of the same type of pose are similar, despite being captured from different points of view.

A compact feature named histograms of 3D joints (HOJ3D) is generate by applying a spherical coordinate system which is aligned to the joints of the person torso, then the zenith angle (Θ) and

azimuth angle (α) are computed and cast into bins, with the spherical coordinate system assuring that each 3D joint falls into a unique bin. The α direction is defined by the vector direction from the left hip joint to the right hip joint, and for Θ direction is defined the floor plane normal vector (Figure 7.10 (a)). For the reference coordinate system center is used the hip center joint.

The 3D space is partitioned into n bins ($n=84$) as shown in Figure 7.10 (b), the inclination angle is divided into 7 bins from the zenith vector α : [0, 15], [15, 45], [45, 75], [105, 135], [165, 180]. Similarly, from the reference vector Θ , the azimuth angle is divided into 12 equal bins of 30° resolution. In order to make the skeleton representation scale-invariant the radial distance is not used.

In summation, the proposed method represents an action as an histogram where each frame of the 20 joints are assign to the correspondent bin followed by its normalization, resulting in 84 features (number of bins) which are used for classification.

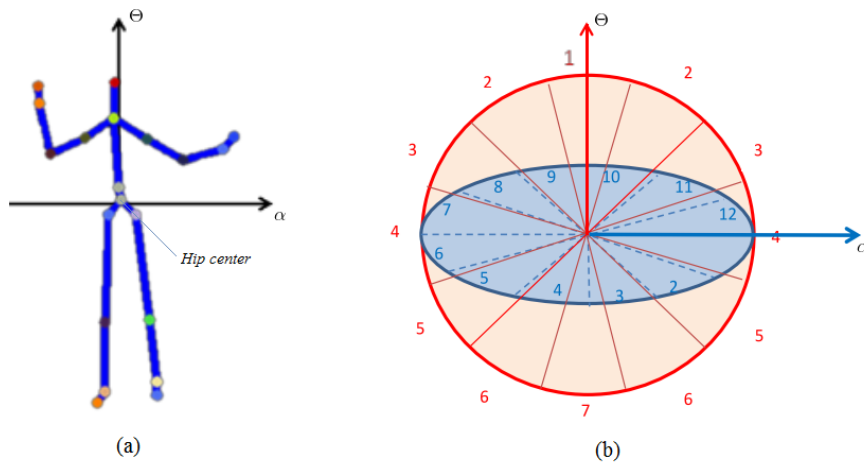


Figure 7.10: (a) Reference coordinates of HOJ3D. (b) Modified spherical coordinate system for joint location binning, (Adapted from [98])

7.3.2 Dataset Description

The dataset from the sessions conduct to test the interfaces present in Chapter 5 could not be used at this point of the study, given the fact that each acquired sequence had to be observed in order to attest its reliability, which were unrealistic to accomplish, given the the time available for this part of the work. Besides, it was imperative to to assess the results for the proposed method with the same dataset and protocol as prior works. In this case, to evaluate the present method, a selection

process of datasets had to check the following requirements:

- The acquisition process should be made with a depth sensor (preferably the Microsoft Kinect) with 3D joint coordinates available per frame;
- The actions performed should somewhat resemble the environment conditions and, more importantly, exercises shown in Chapter 5;
- Available state-of-the-art methods procedure and efficiency for comparison.

Two benchmark datasets, UTD-MHAD (UTD Multimodal Human Dataset) [115] and MSRAction3D [116], were used to assess the proposed method with the results compared to those reported in other papers on the same datasets and under the same training and testing configuration.

UTD-MHAD dataset is collected using a Microsoft Kinect sensor and a wearable inertial sensor in an indoor environment, however only the data acquired with the sensor is used. The dataset contains 27 actions performed by 8 subjects (4 females and 4 males), each subject repeated each action 4 times, in total 861 data sequences (see Table 7.3). This dataset possesses large intra-class variations due to the following reasons:

- (i) Subjects performed the same action at different speeds in different trials;
- (ii) Subjects had different heights;
- (iii) The same action was repeated in a natural way which made each trial slightly different.

Table 7.3: UTD-MHAD dataset actions, (Adapted from [115])

Action name	
1	Right arm swipe to the left
2	Right arm swipe to the right
3	Right hand wave
4	Two hand front clap
5	Right arm throw
6	Cross arms in the chest
7	Basketball shoot
8	Right hand draw x
9	Right hand draw circle (clockwise)
10	Right hand draw circle (counter clockwise)
11	Draw triangle
12	Bowling (right hand)
13	Front boxing
14	Baseball swing from right
15	Tennis right hand forehand swing
16	Arm curl (two arms)
17	Tennis serve
18	Two hand push
19	Right hand knock on door
20	Right hand catch an object
21	Right hand pick up and throw
22	Jogging in place
23	Walking in place
24	Sit to stand
25	Stand to sit
26	Forward lunge (left foot forward)
27	Squat (two arms stretch out)

MSRAction3D dataset is composed by 3D joint positions and depth sequences captured with a depth camera. Twenty actions were performed two or three times by ten subjects, the frame rate is 15 frames per second with a resolution of 320×240 . Altogether, the dataset has 557 joint sequences in total. The 3D joint positions were extracted from the depth sequence by using the real time skeleton tracking algorithm proposed by *Shotton et al.* [97]. The dataset is grouped in three different groups (see Table 7.4), where AS1 and AS2 were intended to group actions with similar

movement, while AS3 was intended to group complex actions together. For instance, action *hammer* is likely to be confused with *forward punch* and, action *pickup & throw* is a composition of *bend* and *high throw* in AS1.

Table 7.4: The three subsets of actions used in the experiments, (Adapted from [116])

Action Set 1		Action Set 2		Action Set 3	
AS1		AS2		AS3	
2	Horizontal arm wave	1	High arm wave	6	High throw
3	Hammer	4	Hand catch	14	Forward kick
5	Forward punch	7	Draw x	15	Side kick
6	High throw	8	Draw tick	16	Jogging
10	Hand clap	9	Draw circle	17	Tennis swing
13	Bend	11	Two hand wve	18	Tennis serve
18	Tennis serve	12	Forward kick	19	Golf swing
20	Pickup & throw	14	Side boxing	20	Pickup & throw

7.4 Experimental Results

The following section describes the results obtain with the proposed method in two different datasets, the first experiment was conducted using the UTD-MHAD dataset and the for the second experiment was used MSRAction3D dataset. All the experiments were compare to state-of-the-art methods with information regarding the test evaluation procedure.

7.4.1 Experiment number one

The first experiment used the work of *Chen et al.* [115] in UTD-MHAD dataset for comparison with the proposed method. *Chen et al.* method proposed the tests to be performed with data from the subject numbers 1, 3, 5, 7 for training, and the data for the subject numbers 2, 4, 6, 8 for testing. The model validation technique was not mention so it was used a 5-fold cross validation.

The SVM classifiers were trained with linear and quadratic kernel functions with “one-versus-one” approach. For all these cases were tested with increasing exponential sequences of C , from $C = 2^{-2}$ to $C = 2^6$. The best results were for a Quadratic SVM with $C = 2^1$, with an accuracy of 56.05%.

The k NN classifier used was a Weighted k NN with distance euclidean and distance weight: inverse and squared inverse, for all this cases $k=1,...,12$ was tested. The best accuracy achieved was 53.72%, with squared inverse distance weight and $k=10$.

The proposed method with SVM and k NN classifier compared with *Chen et al.* method (see Table 7.5) is outperformed by 10.05% and 12.38%, respectively.

The accuracy difference between both classifiers is marginal (2.33%), the Figure 7.11 illustrates that some actions are better predicted with SVM classifier and for other actions the k NN is

Table 7.5: Human action recognition accuracy comparison for UTD-MHAD dataset

Method	Accuracy
<i>Chen et al.</i>	66.10%
Proposed Method (with SVM classifier)	56.05%
Proposed Method (with k NN classifier)	53.72%

more accurate. The method with classifier SVM only 5 actions have an accuracy higher than 75%, with only 2 actions completely correct (Right hand pick up and throw and Jogging in place) and, for the method with classifier k NN have 6 actions with an accuracy higher than 75% and none is entirely accurate.

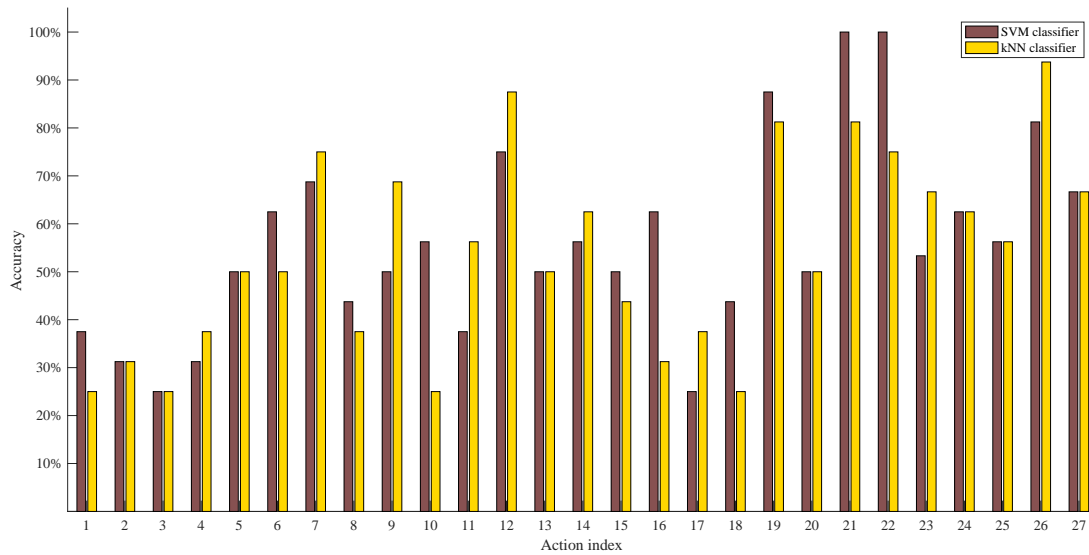


Figure 7.11: Comparison between the accuracy of the proposed method with classifier SVM and classifier k NN

The confusion matrix was done for both classifiers (see Appedix H, Figure H.1 and Figure H.2), and some measures were calculated regarding the information provided by the matrices of confusion (see Table 7.6), such as: precision, recall, specificity and F-score. The accuracy was already compared and shown minimal difference, this trend maintains for the rest of the parameters calculated. The parameters for precision, recall and F-score are ever so slightly better with a SVM classifier and, the specificity is tied between both methods. For more detail, the following aspects were extracted from Table 7.6:

- The SVM classifier has better precision in 14 actions, in 11 action the classifier k NN is better and for 2 actions the precision is tied;

- The proportion of positives currently identified is practically the same for the same classifiers, the classifier k NN is better for 9 actions and the SVM classifier for 10 actions, where 8

actions has the same value;

- The negatives currently identified are very similar for both classifiers, the classifier kNN is better for 8 actions and the SVM classifier for 11 actions, where 8 actions has the same value;

- When combining the precision and recall the SVM classifier has a higher score for 16 actions and the scores for 10 actions as a F-score higher with the classifier kNN .

Table 7.6: Statistics extracted from the confusion matrices of the methods with classifier SVM and kNN

Action index	Precision		Recall		Specificity		F-score	
	kNN	SVM	kNN	SVM	kNN	SVM	kNN	SVM
1	0.25	0.29	0.25	0.38	0.97	0.96	0.25	0.32
2	0.63	0.63	0.31	0.31	0.99	0.99	0.42	0.42
3	0.27	0.44	0.25	0.25	0.97	0.99	0.26	0.32
4	1.00	1.00	0.38	0.31	1.00	1.00	0.55	0.48
5	0.73	0.62	0.50	0.50	0.99	0.99	0.59	0.55
6	0.62	0.67	0.50	0.63	0.99	0.99	0.55	0.65
7	0.57	0.52	0.75	0.69	0.98	0.98	0.65	0.59
8	0.67	0.88	0.38	0.44	0.99	1.00	0.48	0.58
9	0.52	0.35	0.69	0.50	0.98	0.96	0.59	0.41
10	0.36	0.32	0.25	0.56	0.98	0.95	0.30	0.41
11	0.39	0.40	0.56	0.38	0.97	0.98	0.46	0.39
12	0.61	0.86	0.88	0.75	0.98	1.00	0.72	0.80
13	0.38	0.62	0.50	0.50	0.97	0.99	0.43	0.55
14	0.71	0.64	0.63	0.56	0.99	0.99	0.67	0.60
15	0.58	0.53	0.44	0.50	0.99	0.98	0.50	0.52
16	0.63	0.42	0.31	0.63	0.99	0.97	0.42	0.50
17	0.60	0.27	0.38	0.25	0.99	0.97	0.46	0.26
18	0.29	0.54	0.25	0.44	0.98	0.99	0.27	0.48
19	0.30	0.50	0.81	0.88	0.93	0.97	0.44	0.64
20	0.29	0.36	0.50	0.50	0.95	0.97	0.36	0.42
21	0.76	0.70	0.81	1.00	0.99	0.98	0.79	0.82
22	0.80	0.67	0.75	1.00	0.99	0.98	0.77	0.80
23	1.00	1.00	0.67	0.53	1.00	1.00	0.80	0.70
24	0.45	0.67	0.63	0.63	0.97	0.99	0.53	0.65
25	0.75	0.90	0.56	0.56	0.99	1.00	0.64	0.69
26	0.94	0.93	0.94	0.81	1.00	1.00	0.94	0.87
27	0.91	0.83	0.67	0.67	1.00	1.00	0.77	0.74
Average	0.59	0.61	0.54	0.56	0.98	0.98	0.54	0.56
SD	0.23	0.22	0.21	0.20	0.02	0.01	0.18	0.16

In resume, for this study the process to choose the best classifier evolved several parameters. The selected parameters showed that the SVM classifier only performs better ever so slightly compared with kNN classifier. However, the SVM classifier requires higher computational power thus, slower compared with kNN classifier. In this case, it is convenient do a trade-off between marginal accuracy for a faster method.

7.4.2 Experiment number two

In this experiment the proposed method was tested with MSRAAction3D dataset. The classifier for this experiment is an Weighted k NN classifier with distance euclidean and squared inverse distance weight. It was the one with best accuracy for the Weighted k NN with distance euclidean and distance weight: inverse and squared inverse, with the number of neighbours between 1 and 12. The experimental tests conduct in this dataset were compared to the work of *Li et al.*[117], where the tests performed used different number of training samples in order to evaluate the performance of the proposed method. Each experiment were repeated 10 times randomly splitting training and testing data and, the mean performance is reported in Table 7.7. More specific the average recognition accuracies when one third of the samples, two third of the samples and cross-validation from half of subjects samples were used as training, with a 5-fold cross validation for the training model. The results have shown that *Li et al.* method outperforms by a large margin the proposed method in all the tests. For the proposed method, all the best results happen in test two, which is not at all unsurprising because is the test with more training actions. In other hand, the worst performances happen when all the actions are used, with the lowest accuracy being the cross subject test (35.61%).

Table 7.7: Recognition accuracies of different tests. In test one, 1/3 of the samples were used as training samples and the rest as testing samples; in test two, 2/3 samples were used as training samples and the rest as testing samples; and in the cross subject test, half of the subjects were used as training and the rest subjects were used as testing

	Test One		Test Two		Test Three	
	<i>Li et al</i>	k NN	<i>Li et al</i>	k NN	<i>Li et al</i>	k NN
AS1	89.50%	61.54%	93.40%	73.56%	72.90%	61.45%
AS2	89.00%	58.43%	92.90%	77.10%	71.90%	48.51%
AS3	96.30%	60.81%	96.30%	75.14%	79.20%	65.43%
All	91.6%	42.97%	94.2%	55.68%	74.7%	35.61%

The confusion matrix for one of the tests performed (where 2/3 of the samples are used as training) for the groups AS1, AS2 and AS3 are shown in Figure 7.12, Figure 7.13 and Figure 7.14, respectively. Previously, it was mentioned that the *Pick up & throw* action was a composition of the actions *Bend* and *Tennis serve*, the confusion matrix shows that this actions get mix up with each other (see Figure 7.12), for instance the *Bend* action is accurately 66.67% of the times and, wrongly predicts *Tennis serve* action (11.11%) and *Pick up & throw* action (22.22%). The set AS2 (Figure 7.13) is clear that the classifier as trouble in distinguish the actions *Hand catch*, *Draw X*, *Draw tick* and *Draw circle*. For instance, the action *Draw circle* is 55.56% accurately, and is classified wrongly with the actions *Draw X* (22.22%) and *Draw tick* (22.22%). Lastly, the set AS3 (see Figure 7.14) composed with more complex actions the pattern of misclassified actions are not as condensed to two or three actions. For example, the *Pick up & throw* action is incorrectly classified as *High throw* (6.25%), *Side Kick* (6.25%), *Tennis swing* (6.25%) and *Golf*

swing (18.75%).

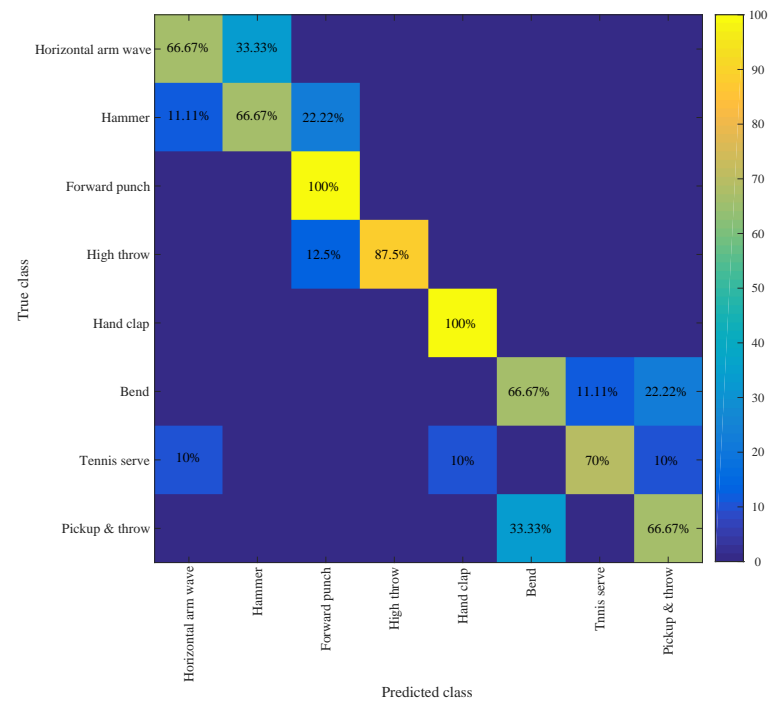


Figure 7.12: Confusion matrix of k NN: Test Two, AS1

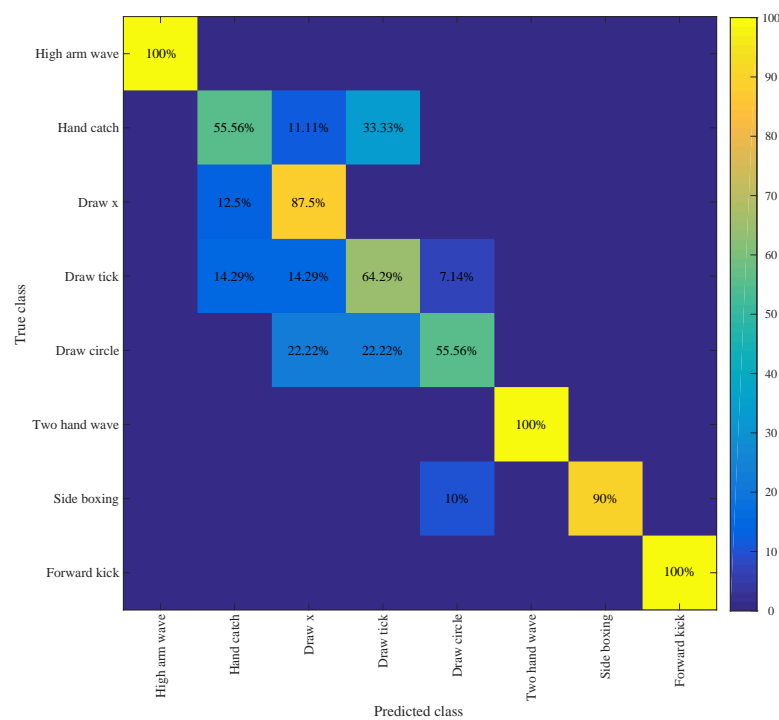
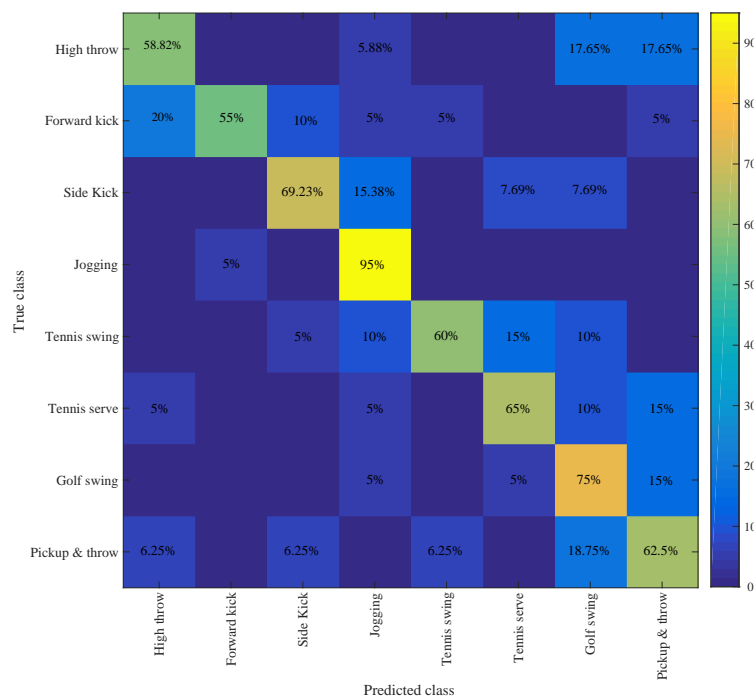


Figure 7.13: Confusion matrix of k NN: Test Two, AS2

Figure 7.14: Confusion matrix of k NN: Test Two, AS3

7.5 Summary

Over the past few years, the interest in Human action recognition has growing enormously since it may enable different applications, from the most commercial (gaming or HCI) to the most assistive ones however, action recognition in unconstrained settings still remains a challenge. In order to simplify this problem research has been made in what type hardware to use for actions acquisition, which evolved from using cameras to more sophisticated sensors such as Microsoft Kinect which can locate human body joints and produce moving 3D skeletons [118].

In this chapter, a simple activity recognition algorithm has been proposed to recognize human action as space time of representative 3D poses (space time approach). It is based on skeleton data extracted from an depth or RGBD sensor, where a histogram (hoj3d) is created by casting each joint of the skeleton to a single bin within a modified spherical coordinate system thus, representing the whole action.

The experimental results show that the method implemented is not able to overcome state-of-the-art results in two publicly available datasets, the UTD-MHAD dataset and MSRAAction3D dataset. However, the time available for this study was very short which let to the development of a quite simple method.

The conclusion withdrawn from the experimental results is the need to improve overall accuracy which could be accomplish by revisiting the feature selection (see Figure 7.15) where the

following changes could be performed:

- Selecting just skeleton joints relevant to the actions;
- Perform feature reduction.
- Then, using more complex classifiers. During the review of the available classifiers were mention that k NN and SVM are usually used for space time approach, hence testing polynomial SVMs should be taken in account has an alternative;
- Test the proposed method with the dataset collect in the work of interfaces development.

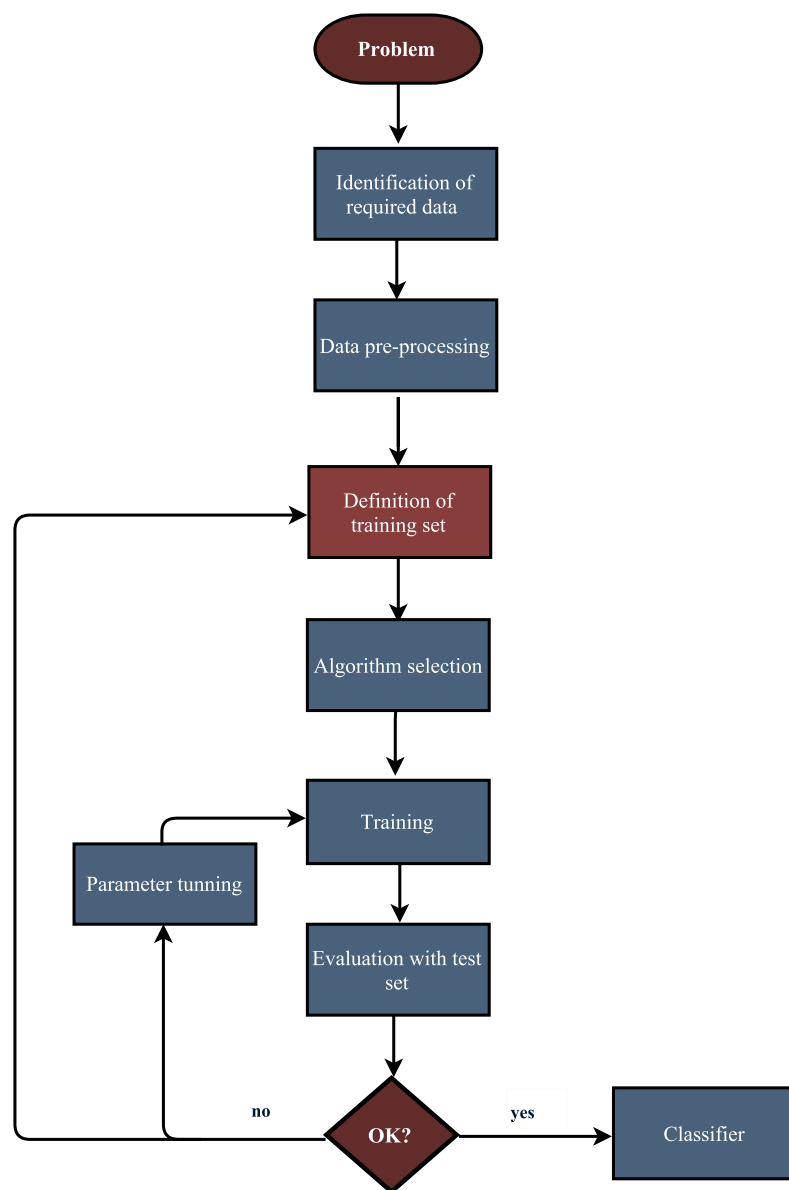


Figure 7.15: Process for further improvement of the accuracy in the proposed method, (Adapted from [107])

Chapter 8

Conclusion and Future Work

This final chapter includes two sections, in which are presented a concise conclusion of this investigation and then some conceivable suggestions, in order to improve this work in the future.

8.1 Conclusion

Nowadays, all around the world breast cancer is the most common on female population, being ranked the fifth death cause, with an average survival rate of 61% after five years of diagnoses [93]. Over 60% of patients report at least one functional impairment during or after treatment for breast cancer, outcome of several side effects resulting from the practice of surgical procedures followed by chemotherapy and radiation therapy [80], which are proven to lowering the UBF and frequently accompanied with the presence of lymphedema and severe pain in arm-shoulder having a direct impact in the overall QOL of woman. Thus, is the utmost importance, to create some sort of strategy to combat and enable its symptoms as early on as possible.

Over the past decades, the HCI with interfaces is considered an emergent field in the industry and has opened the way to communicate with the means of verbal, hand and body gestures using the latest technologies for a conjunction of various applications in areas such as video games, training and simulation [69]. Also, within HCI, serious games became rapidly growing industry with impact in areas such education, engineering and healthcare. The general idea is to combine the principles of games with the added purpose of pedagogical and improvement of a certain aspect.

The impact of this particular HCI fields could not be possible without accessible and innovative technological tools, within game development several game engines are available offering a series of options such as integration with NUI devices, as an example the game engine Unity offers integration with Microsoft Kinect [62]. Also, in developing and deploying a serious game other industry-standard tools play an important role in order to make the interaction as fulfilling and engaging as possible. Not having to go very far, in this work the developing process of the present interfaces were not restricted only to the game engine, for example Autodesk Maya was used for avatar animation.

With all that was mentioned, the present work was mostly aimed at develop and test a series of interfaces with the main focus being improvement of UBF in the early stages of the rehabilitation period, having physical exercise at its core as one of the ways to prevent/enable the harmful effects of breast cancer prior mention. The idea is to not overwhelm the senses or tire the user, but instead find optimal, efficient, and natural interfaces for immersive environments. Thus, several aspects became the focus of this work such as visual and temporal feedback. For visual feedback various options were developed: no visual feedback, avatar-based feedback and mirror-based feedback. With the avatar-based feedback subdivided in three different levels of abstraction. All of the developed interfaces as a common set of components and the same fluidity and efficiency level, with the purpose of not skew the results of the evaluation carried out.

The test and evaluation of the interfaces were done in sessions at Hospital S. João, with the study population breast cancer survival patients, where the main source of assessment was the filling out of a proposed questionnaire at the end of each session. Overall, the interfaces were well received with visual feedback being largely preferred. Within visual feedback, an overwhelming choice fell into avatar-based feedback opposed to mirror-feedback. Also, it was collect a set of suggestions with the most votes cast in having an application with the option of multi-player and having more information about the performance of the user during the game.

The work that followed had in mind the suggestions gather from the study population, so given the preference for avatar-based feedback a interface with multi-player was developed, although has its problems already mention, that it is not possible to guarantee that the avatar cast to a user maintains assign to the same user when the sensor as a period were it does not detect both users.

Then, the focus resided in studying the accuracy of the Microsoft Kinect in calculating angles of the shoulder and elbow in specific poses and the possibility of using it instead of a tradition instrument the goniometer, also allowing to assess the accuracy of the sensor in detecting the skeleton joints when its vision is not occluded. For this study, an interface were developed in order to be as intuitive as possible. Two separated sessions were performed for different measures, in order to prevent the user cases from making more movements due to fatigue or annoyance, the results compared to the goniometer led to the conclusion that the Microsoft Kinect can be used as a possible substitute, however its not conceivable make interjections about a high level of accuracy because the broad error that the goniometer has.

Lastly, the emphasise of this work were towards human action recognition which is a key problem in computer vision with latent impact in human-robot interaction, elderly assistance systems, and gaming, just to name a few. The main objective was to do a study towards a method for recognition of actions and substitute the method prior implemented which are based in a set of rules and its accuracy strongly depends from user to user. The method implemented does not has a high accuracy although as potential, given the little time and not near enough this part of the work deserves.

In short, the design, development and evaluation of the proposed interfaces had in mind the best possible application for rehabilitation of patients with breast cancer in order to prevent long-term impairments, the work that followed this assessment had the sole purpose to improve certain

aspects of the proposed interfaces. Overall, the feedback was positive and it was possible to estimate certain aspects that may lead to a clearer idea of what the target public wants in such application.

8.2 Future Work

In this research, very promising results were accomplished regarding the interfaces implemented for the rehabilitation period, nonetheless some improvements can still be pointed out. Thus, some suggestions for future research that can contribute to resolve some unfinished aspects of this work:

- Carry out the suggestions done in Chapter 6 for further assessment in using the Microsoft Kinect as a medical tool;
- Continue the work in human action recognition, in order to improve its accuracy and, testing with the dataset collected;
- Implement in the final interface the method developed in human action recognition;
- Expand the database with a more diversified set of data by testing the final product.

Appendix A

Interfaces Protocol

A.1 Protocol for interfaces: Single-player

This protocol is for the following interfaces:

- Interface with no visual feedback
- Interface with mirror-based feedback
- Interface with skeleton avatar-based feedback
- Interface with humanoid avatar-based feedback
- Interface with humanoid avatar-based feedback (sparse activity)
- Interface with personalized avatar-based feedback

Protocol steps:

1. Connect the Kinect to the computer and power supply
2. Double-click the game executable and choose 1600x900 resolution (in order to avoid formatting issues)
3. Place the USERNAME (letters, numbers and spaces)
 - 3.1) If the instructions button is press, the instruction manual appears on how to play the game
4. Press the <START> button to begin the game
5. Select the Avatar (in case of the interface with (personalized) avatar-based feedback)
6. In the game environment make sure that the Kinect to detect the user range of motion
 - 6.1) There is an input field to tilt the sensor
7. Start the exercise by pressing the <SPACE>
8. Change the exercise by pressing the <SPACE>
9. At the end of exercises some statistics appear

10. Finally, there is an option to leave the game by clicking the <EXIT> or return to the main menu to perform another session

A.2 Protocol for interfaces: Multi-player

Protocol steps:

1. Connect the Kinect to the computer and power supply
2. Double-click the game executable and choose 1600x900 resolution (in order to avoid formatting issues)
3. Place the USERNAME (letters, numbers and spaces) for player 1 and player 2
 - 3.1) If the instructions button is press, the instruction manual appears on how to play the game
4. Press the <START> button to begin the game
5. Select the Avatar for player 1 and player 2
6. In the game environment make sure that the Kinect to detect the user range of motion for both players before start the exercise
 - 6.1) There is an input field to tilt the sensor
7. Start the exercise by pressing the <SPACE>
8. Change the exercise by pressing the <SPACE>
9. At the end of exercises some statistics appear for both players
10. Finally, there is an option to leave the game by clicking the <EXIT> or return to the main menu to perform another session

A.3 Acquisition Environment

The acquisitions room dimensions were:

- **Length:** 3.76m
- **Width:** 2.60m

Appendix B

Interfaces Requirements

B.1 Kinect and Unity system

B.1.1 Hardware requirements

The sensor should be connect to a computer with the following minimum requirements:

- Windows 7, Windows 8, Windows Embedded Standard 7, Windows Embedded POS-Ready 7 or Windows 10
- 32 bit (x86) or 64 bit (x64) processor
- Dual-core 2.66-GHz or faster processor
- USB 2.0
- 2 GB RAM
- Microsoft Kinect Software Development Kit (SDK) or Kinect Runtime

B.1.2 Limits

In order to archieve the best aquisition/experience the following limits of the Microsoft Kinect needs to be taken in count:

- Horizontal viewing angle: 57
- Vertical Viewing Angle: 43
- User Distance: 1.2m to 4m
- Depth range: 0.4m to 8m
- Temperature: 5 to 35 degrees Celsius
- Engine tilt angle sensor: -27 to +27

B.1.3 Skeleton Joints

Standard information about the skeleton positions acquire by the Microsoft Kinect:

- A skeleton contains 20 joints.
- The 3D position of each joint of the skeleton are stored as coordinates (X, Y, Z).
- Each X, Y coordinate and Z is the distance in meters from the sensor.
- In standard mode (full skeleton) Kinect tracks 20 joints.
- In the sitting mode Kinect tracks only the joints 10 of the upper body.
- The placement of Kinect on a surface that is not level may generate skeletons inclined leaning rather than meeting in a vertical position.

B.1.4 Position of the Sensor

- The sensor must be position between 1m to 1.8m in front of and used at a distance of 0.6m up to 1.8m from the floor (depending on the size of the user) and with nothing between the sensor and user.
- In the whole range of the sensor only the user(s) must be detected.
- Nothing shall prevent the sensor automatically tilt up or down.
- The sensor should not be placed on or in front of a loudspeaker or on a surface that vibrates or makes noise.

B.1.5 Room environment

- The sensor works with all types of lighting (even without light), however it works better with moderate light. Thus the space must have enough light to the face patient is visible and evenly illuminated. The back-light, especially from a window should be avoided.
- Ideally, the light should come from behind the sensor.
- The skeleton tracking is less reliable with large amounts of natural light.

B.2 Saving Data

B.2.1 Files Organization

A folder is created inside the folder of the respective interface with the input done in the begin of the game (username) and the present date, inside folders are created with the name *ExerciseX*. On each folder a .csv file has the skeleton positions, and time-stamp for each frame register. And color frames with the respective time-stamp.

B.2.1.1 .csv file

The .csv file has the following scheme:

- The first column has the time stamp.
- The second column has the skeleton position index.
- The third, fourth and fifth columns have the (X, Y, Z) coordinates, respectively.

Appendix C

Personalized Avatar

C.1 Software used for acquisition

In order to obtain a personalized avatar the following programs were used:

- *Fast Avatar Capture* [119]
- *Autorigger and Reshaper* [120]

C.2 Protocol used for acquisition

A different approach was applied when using the *Fast Avatar Capture*, the original protocol mention for the user to rotate four times 90 degrees to the left (when the voice control given the instruction). Instead the Microsoft Kinect was attached to a tripe (approximately 1m high), being the one to rotate alternatively to the user. Then, the obtain mesh was exported to *Autorigger and Reshaper*, where its rig was performed resulting in a *.dae file*. Lastly, the COLLADA file was incorporated in Unity (see Figure C.1).

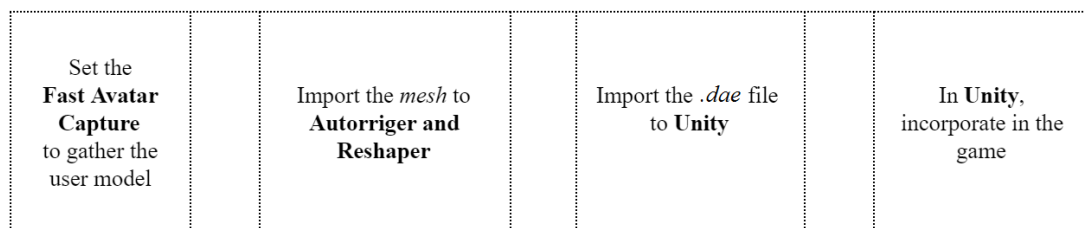


Figure C.1: Acquisition process for the personalized avatar

Appendix D

Informed consent

Faculdade de Engenharia da Universidade do Porto
INESC-TEC
Centro Hospitalar São João

Departamento de Engenharia Eletrotécnica e de Computadores
Mestrado Integrado em Engenharia Eletrotécnica e de Computadores
Unidade Curricular de Dissertação
Ano letivo de 2016/2017

Declaração de Consentimento Informado

Título do Estudo: Uma abordagem interativa para a reabilitação de pacientes com cancro de mama

Autor do estudo: Carolina Lopes

Eu, abaixo-assinado, compreendi a explicação sobre o objetivo do estudo que se pretende realizar, bem como as suas implicações. Tive oportunidade de esclarecer qualquer tipo de dúvidas relativamente aos procedimentos, obtendo uma resposta satisfatória. Entendi que o método de avaliação de resultados do estudo não traz qualquer risco para a minha saúde. Foi-me garantido o anonimato, não havendo possibilidade de ser identificada qualquer informação pessoal. Tenho o direito de recusar a minha participação no estudo a qualquer momento. Deste modo, consinto participar no estudo.

Data:/...../2016

Assinatura do sujeito:

Assinatura do autor do estudo:

Appendix E

Questionnaire

E.1 Questionnaire for patients with breast cancer

Questionário do utilizador

- No âmbito da realização da dissertação no Mestrado Integrado em Engenharia Electrotécnica e Computadores na Faculdade de Engenharia da Universidade do Porto em conjunto com o INESC-TEC e o Centro Hospitalar São João, este questionário tem como principais objetivos a avaliação e aferição das diferentes interfaces expostas.
Obrigado pelo preenchimento deste questionário.

* Required

Autorização da utilização das informações cedidas

Os dados obtidos na realização deste questionário serão utilizados como forma de avaliação da melhor interface para o período de reabilitação. Garantindo ao longo deste processo o anonimato dos seus usuários.

Aceita a recolha e utilização dos dados? *

☐ Sim

☐ Não

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Figure E.1: Questionnaire: Section 1 - Authorization for the use of information provided

Questionário do utilizador

* Required

Caracterizar a população

Nome *

Your answer

Idade *

Your answer

Peso *

Your answer

Altura *

Your answer

Doenças do ombro prévias (tendinites, cirurgias, hérnias coluna cervical, etc) *

☐ Sim

☐ Não

Figure E.2: Questionnaire: Section 2, part 1 - Characterization of the population

Cirurgia realizada na mama

- ☐ Mastectomia com reconstrução
- ☐ Mastectomia sem reconstrução
- ☐ Cirurgia conservadora simples
- ☐ Cirurgia conservadora com redução mamária

Cirurgia na axila

- ☐ Gânglio sentinela
- ☐ Esvaziamento axilar

Complicações

- ☐ Não
- ☐ Seroma
- ☐ Hematoma
- ☐ Infecção
- ☐ Hemorragia
- ☐ Necrose
- ☐ Other: _____

Radioterapia

- ☐ Sim
- ☐ Não

Quimioterapia

- ☐ Sim
- ☐ Não

Figure E.3: Questionnaire: Section 2, part 2 - Characterization of the population

Fisioterapia

- ☐ Sim
- ☐ Não

Linfedema

- ☐ Sim
- ☐ Não

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Figure E.4: Questionnaire: Section 2, part 3 - Characterization of the population

Questionário do utilizador

* Required

Informações pessoais

Idade *

Your answer

Estado civil *

- ☐ Solteira
- ☐ União de facto
- ☐ Casada
- ☐ Divorciada
- ☐ Viúva

Nível académico *

- ☐ Sem escolaridade
- ☐ 4º ano de escolaridade
- ☐ 6º ano de escolaridade
- ☐ 9º ano de escolaridade
- ☐ 12º ano de escolaridade
- ☐ Bacharelato
- ☐ Licenciatura
- ☐ Mestrado
- ☐ Doutoramento

Figure E.5: Questionnaire: Section 3, part 1 - Personal information

Situação profissional *

- ☐ Estudante
- ☐ Empregada
- ☐ Desempregada
- ☐ Reformada

Em média, quanto tempo livre tem por semana?

	1	2	3	4	5	
Nenhum	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Muito

Para a realização dos exercícios em casa usaria alguma das interfaces apresentadas?

- ☐ Sim
- ☐ Não
- ☐ Talvez

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Figure E.6: Questionnaire: Section 3, part 2 - Personal information

Questionário do utilizador

* Required

Relação com Novas Tecnologias

Tem recursos tecnológicos que normalmente usa em casa?
(Computador, tablet, smartphone ...) *

- ☐ Sim
- ☐ Não

Se respondeu "Sim", indique quais?

- ☐ Computador
- ☐ Consola de jogos (Playstation, X-Box, Wii, entre outros)
- ☐ Tablet
- ☐ Smartphone
- ☐ Outros

Com que frequência joga nos recursos tecnológicos que possui?

- ☐ Nunca
- ☐ Uma ou duas vezes por mês
- ☐ Uma ou duas vezes por semana
- ☐ Todos os dias

Figure E.7: Questionnaire: Section 4, part 1 - Relation with new technologies

Alguma vez jogou um jogo sério? *

☐ Sim

☐ Não

Se respondeu "Sim", indique qual?

Your answer

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Figure E.8: Questionnaire: Section 4, part 2 - Relation with new technologies

Questionário do utilizador

* Required

Avaliação das interfaces propostas

Nesta secção, é solicitada uma avaliação geral das interfaces
(1- Corresponde a "nada" 5- Corresponde a "muito")

Entre as interfaces apresentadas, na sua opinião qual poderá
ser o mais útil/eficaz no período de reabilitação? *



☐ a) Interface sem Avatar e sem projeção do utilizador



☐ b) Interface com projeção do utilizador



☐ c) Interface com projeção de esqueleto



☐ d) Interface com Avatar

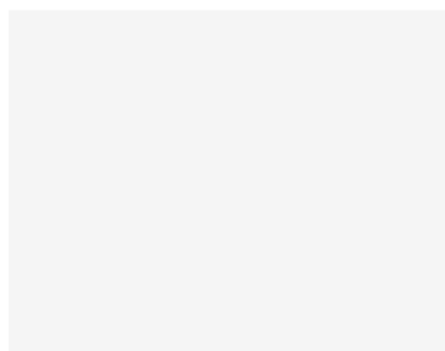
Figure E.9: Questionnaire: Section 5, part 1 - Evaluation of proposals interfaces



☐ e) Interface com Avatar personalizado



☐ f) Interface com Avatar s/projeção do exercício



☐ Nenhuma das soluções acima mencionadas

De acordo com a sua preferência atribua a sua classificação para cada interface de 1 a 5 *

	1	2	3	4	5
a) Interface sem Avatar e sem projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
b) Interface com projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
c) Interface com projeção de esqueleto	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d) Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
e) Interface com Avatar s/projeção do exercício	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
f) Interface com Avatar personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure E.10: Questionnaire: Section 5, part 2 - Evaluation of proposals interfaces

De acordo com a sua preferência atribua a sua classificação para cada interface de 1 a 5 *

	1	2	3	4	5
a)Interface sem Avatar e sem projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
b)Interface com projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
c)Interface com projeção de esqueleto	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
e)Interface com Avatar s/projeção do exercício	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
f)Interface com Avatar personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

No período de reabilitação, quantifique a contribuição da interface preferida para a realização dos exercícios? *

	1	2	3	4	5	
Contribui em nada	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Contribui em muito

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Figure E.11: Questionnaire: Section 5, part 3 - Evaluation of proposals interfaces

Questionário do utilizador

* Required

Relação com o Ambiente Virtual

Nesta seção, só as interfaces com o Avatar e Avatar personalizado.

1- Corresponde a "nada"

5- Corresponde a "muito"

O avatar representa bem o movimento efetuado por si? *

	1	2	3	4	5	
Nada	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Muito

Qual o contributo das interfaces apresentadas na percepção do movimento efetuado? *

	Piorou	Não auxiliou em nada	Auxiliaram
a)Interface sem Avatar e sem projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
b)Interface com projeção do utilizador	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
c)Interface com projeção de esqueleto	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
e)Interface com Avatar s/projeção do exercício	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
f)Interface com Avatar Personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure E.12: Questionnaire: Section 6, part 1 - Relationship with the virtual environment

No ambiente virtual, até que ponto sentiu que o seu Avatar é uma extensão do seu corpo? *

	1	2	3	4	5
c)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar Personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Quando algo acontece ao corpo do seu Avatar, até que nível fica com a impressão que esta acontecer ao seu corpo? *

	1	2	3	4	5
c)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar Personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Quando se encontra no ambiente virtual, até que ponto se sente dentro do jogo pelo seu Avatar? *

	1	2	3	4	5
c)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar Personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Quando se encontra no ambiente virtual, quanto é que sente o Avatar como parte do seu corpo? *

	1	2	3	4	5
c)Interface com Avatar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
d)Interface com Avatar Personalizado	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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Figure E.13: Questionnaire: Section 6, part 2 - Relationship with the virtual environment

Questionário do utilizador

* Required

Considerações/Sentimentos após a demonstração das interfaces

Durante a demonstração das interfaces como se estava a sentir? Escolha 3 opções *

- ☐ Aborrecida
- ☐ Feliz
- ☐ Irritada
- ☐ Entretida
- ☐ Desafiada
- ☐ Relaxada
- ☐ Eu pensei que era difícil
- ☐ Eu estava completamente ocupada com o jogo
- ☐ Eu pensei sobre outras coisas
- ☐ Eu era boa jogadora
- ☐ Eu senti a pressão do tempo
- ☐ Eu senti-me pressionada
- ☐ Foi esteticamente agradável
- ☐ Pareceu-me uma experiência enriquecedora

Figure E.14: Questionnaire: Section 7, part 1 - Considerations/feelings about the proposals interfaces

Durante a execução dos exercícios, avalie até que ponto conseguiu acompanhar o avatar que demonstra os exercícios?

	1	2	3	4	5	
Não consegui acompanhar	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Conseguir acompanhar

O que achou da velocidade de execução dos exercícios pelo avatar?

- ☐ Muito lento
- ☐ Lento
- ☐ Normal
- ☐ Rápido
- ☐ Muito rápido

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Figure E.15: Questionnaire: Section 7, part 2 - Considerations/feelings about the proposals interfaces

Questionário do utilizador

Sugestões

Que componentes gostaria que fossem adicionados nas interfaces?

- ☐ Menos informação visual
- ☐ Mais informação visual
- ☐ Opção de escolher diferentes ambientes virtuais
- ☐ Opção de escolher diferentes avatars
- ☐ Mais informação de apoio durante a execução do jogo
- ☐ Mais informação sobre o desempenho do usuário durante a execução de exercícios
- ☐ No final de cada exercício, opção de visualizar os movimentos efetuados pelo usuário
- ☐ Opção de poder executar os exercícios com mais um jogador (multijogador)
- ☐ Não adicionava/fazia mais nenhuma alteração
- ☐ Other : _____

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Figure E.16: Questionnaire: Section 8 - Suggestions

Appendix F

Questionnaire answers

In this appendix, its shown the rest of the answers from breast cancer patients.

F.1 Characterization of the study population

Table F.1: Weight

Responses	Occurrences	Percentage
< 50kg	5	2.78%
51kg - 60kg	19	54.17%
61kg - 70kg	25	54.17%
71kg - 80kg	12	54.17%
81kg - 90kg	7	54.17%
≥ 90kg	3	2.78%

Table F.2: Height

Responses	Occurrences	Percentage
< 1.50m	2	2.78%
1.50m - 1.59m	30	41.66%
1.60m - 1.69m	39	54.17%
≥ 1.70m	1	1.39%

Table F.3: Civil status

Responses	Occurrences	Percentage
Divorced	7	9.72%
Married	52	72.22%
Widow	6	8.33%
Single	6	8.33%
Union of fact	1	1.39%

F.2 Relation with new technologies

Additional information on the relation with new technologies.

Table F.4: Serious game

Responses	Occurrences	Percentage
No	72	100%
Yes	0	0%

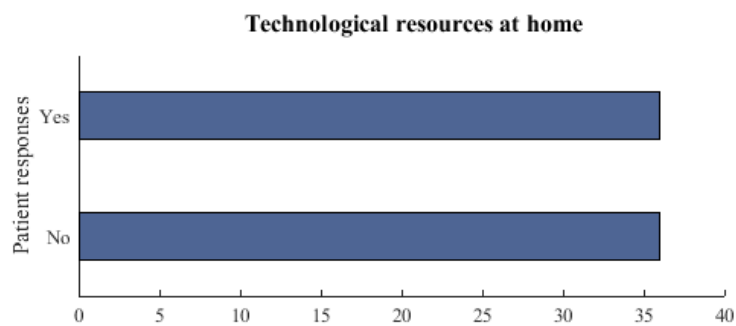


Figure F.1: Technological resources at home

Table F.5: Technological resources

Responses	Occurrences	Percentage
Computer, Tablet, Smartphone	6	8.33%
Smartphone	4	5.56%
Computer	15	20.83%
Computer, Game console, Tablet, Smartphone	3	4.17%
Computer, Smartphone	2	2.78%
Tablet	2	2.78%
Tablet, Smartphone	1	1.39%
Computer, Game console, Tablet	2	2.78%
None	36	50%

F.3 Considerations / feelings after demonstration of interfaces

Table F.6: Considerations / feelings after demonstration of interfaces

Responses	Occurrences	Percentage
Relaxed, I thought it was difficult, It was aesthetically pleasing	1	1.39%
Happy, Entertained, It was aesthetically pleasing	2	2.78%
Entertained, Challenged, Relaxed	1	1.39%
Entertained, It was aesthetically pleasing, It seemed to me an enriching experience	5	6.94%
Happy, Entertained, It seemed like an enriching experience	3	4.17%
Happy, Entertained, Relaxed	5	6.94%
Relaxed, I was completely occupied with the game, It was aesthetically pleasing	2	2.78%
Happy, Relaxed, Aesthetically pleasing	3	4.17%
Entertained, Relaxed, I was completely occupied with the game	4	5.56%
Entertained, I was completely occupied with the game, It seemed to me an enriching experience	6	8.33%
Entertained, Relaxed, It seemed to me an enriching experience	6	8.33%
Entertained, Challenged, It seemed like an enriching experience	1	1.39%
Happy, It was aesthetically pleasing, It seemed to me an enriching experience	1	1.39%
Entertained, Relaxed, Was aesthetically pleasing	1	1.39%
Happy, Relaxed, It seemed like an enriching experience	1	1.39%
Entertained, Challenged, Relaxed	3	4.17%
Entertained, I was completely occupied with the game, It was aesthetically pleasing	5	6.94%
I was completely occupied with the game, It was aesthetically pleasing, It seemed to me an enriching experience	5	6.94%
I thought it was difficult, It was aesthetically pleasing, It seemed to me an enriching experience	1	1.39%
Challenged, It was aesthetically pleasing, It seemed to me an enriching experience	2	2.78%
Angry, Challenged, I felt pressured	1	1.39%
Interactive, Relaxed, I was a good player	1	1.39%
I was completely occupied with the game, I thought about other things, It seemed to me an enriching experience	2	2.78%
Relaxed, It was aesthetically pleasing, It seemed to me an enriching experience	1	1.39%
I was completely occupied with the game, I was a good player, It was aesthetically pleasing	1	1.39%
Happy, I thought it was difficult, It was aesthetically pleasing	1	1.39%
Challenged, Relaxed, I was completely occupied with the game	2	2.78%
Happy, I was completely occupied with the game, It was aesthetically pleasing	1	1.39%
Entertained, I felt the pressure of time, It seemed to me an enriching experience	1	1.39%
Happy, I was completely occupied with the game, It seemed to me an enriching experience	1	1.39%
Happy, Entertained, I was completely occupied with the game	2	2.78%

Appendix G

Goniometer tool simulation

The hardware and physical requirements are exactly the same ones mention in Appendix C.

G.1 Saving Data

G.1.1 Files Organization

A folder is created inside the folder of the respective interface with the input done in the begin by put the username in the input field, inside a folder are created with the name *Measures from dd-mm-aaaa*. On a *.csv* file has the skeleton positions, and time-stamp for each frame register. And color and deph frames with the respective time-stamp. And several screenshots acquired with a 15fps since the begin until the end of the acquisition.

G.1.1.1 .csv file

The *.csv* file has the following scheme:

- The first column has the time stamp.
- The second column has the skeleton position index.
- The third, fouth and fifth columns has the (X, Y, Z) coordinates, respectively.

G.2 Protocol used for acquisition

Protocol steps:

1. Connect the Kinect to the computer and power supply
2. Double-click the interface executable and choose 1600x900 resolution (in order to avoid formatting issues)
3. Place the USERNAME (letters, numbers and spaces)

4. Press the <START> button to begin the acquisition
5. In the interface environment make sure that the Kinect to detect the user range of motion
 - a) There is an input field to tilt the sensor
7. Start the measures by click on the button with the desired angle
8. Then if a particular value wants to be save click in the button <Save measurement>
9. Change the angle acquired by select other option
10. Finally, there is an option to leave the acquisition environment by clicking the <EXIT> or return to the main menu to perform another session

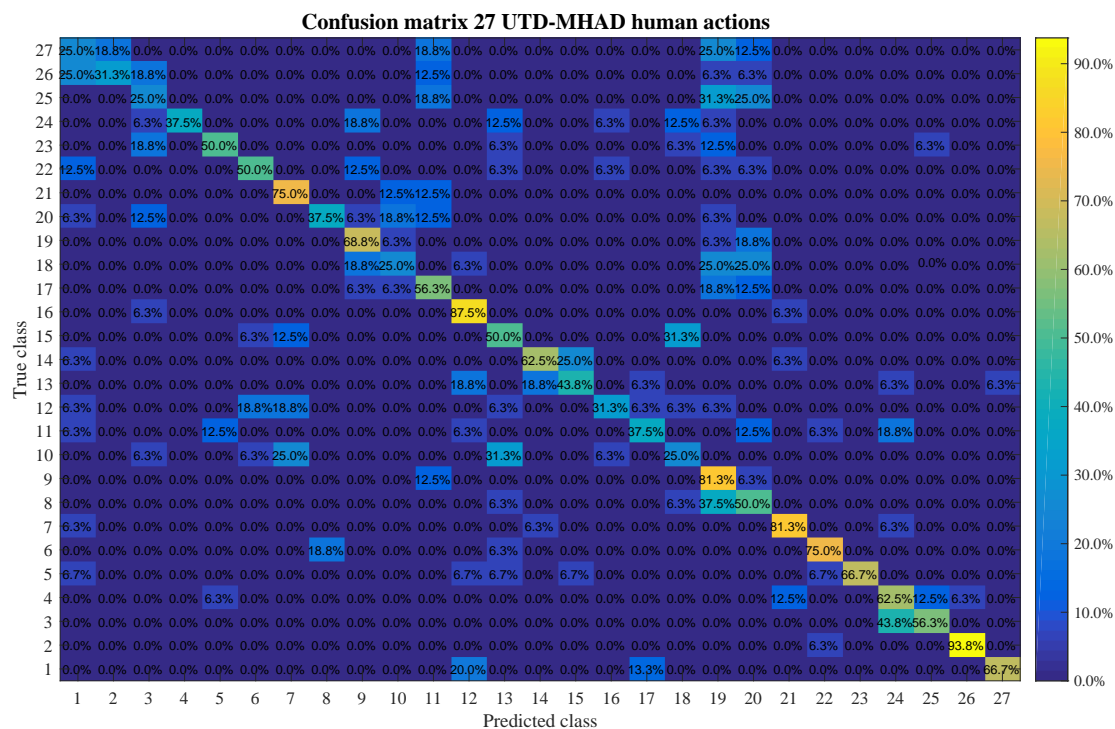
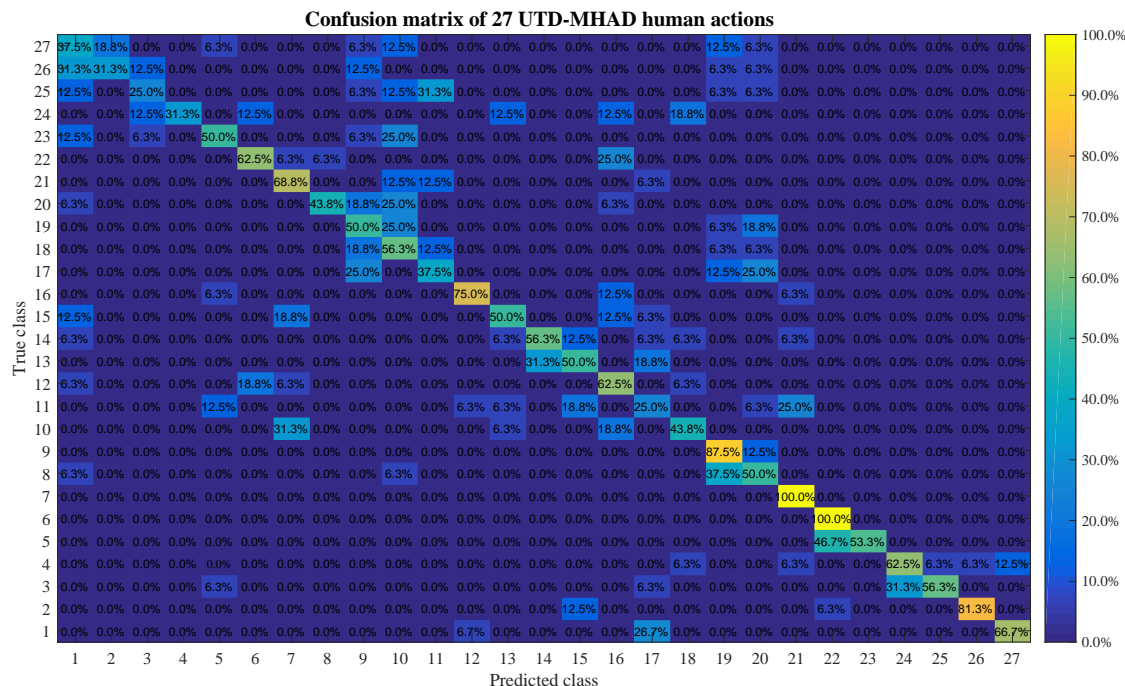
Appendix H

Recognizing Human Activity Using RGBD Data

H.1 Confusion Matrices for tests conduct in UTD-MHAD dataset

Table H.1: UTD-MHAD dataset actions, (Adapted from [115])

Action name	
1	Right arm swipe to the left
2	Right arm swipe to the right
3	Right hand wave
4	Two hand front clap
5	Right arm throw
6	Cross arms in the chest
7	Basketball shoot
8	Right hand draw x
9	Right hand draw circle (clockwise)
10	Right hand draw circle (counter clockwise)
11	Draw triangle
12	Bowling (right hand)
13	Front boxing
14	Baseball swing from right
15	Tennis right hand forehand swing
16	Arm curl (two arms)
17	Tennis serve
18	Two hand push
19	Right hand knock on door
20	Right hand catch an object
21	Right hand pick up and throw
22	Jogging in place
23	Walking in place
24	Sit to stand
25	Stand to sit
26	Forward lunge (left foot forward)
27	Squat (two arms stretch out)



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