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Development and application of experimental software for a 21st century occupational psychophysics research toolbox

Department of Kinesiology and Physical Education

DEVELOPMENT AND APPLICATION OF EXPERIMENTAL SOFTWARE FOR A 21ST CENTURY OCCUPATIONAL PSYCHOPHYSICS RESEARCH TOOL-BOX

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Dedication

This thesis is dedicated to my parents, the two individuals I will forever be in debt to. Thank you for raising me to be the person I am today, and for the countless sacrifices you have had to make over the years just so your children could have a better future than you ever had.

Abstract

In the fields of ergonomics and biomechanics, the use of bio-instrumentation for the purpose of analysing work and reducing work related muskuloskeletal disorders for injury prevention has become a new norm. It is equally important to employ these instruments in ecologically-valid experimental work tasks that use relevant and controllable manipulations of occupational psychophysics. The current thesis attempts to begin design and validation of components for a 21st century occupational psychophysics toolbox that couples relevant bio-instrumentation hardware (vision tracking, motion capture, and force platforms) with custom Matlab based experimental software capable of image processing, assessment of full body kinematics, and analysis of ground reaction force kinetics to study the perceptions and actions at work tasks. I investigated the coupling between visual attention and cueing, pre-handling perceptions, and manual material handling actions, with the ultimate goal of understanding occupational behaviours and preventing injurious occupational behaviours.

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Thank you to Dr. Jon Doan, my supervisor, without whose support I couldn’t have accomplished what I have been able to over the past 4 years. Thank you for believing in me and my abilities, and providing me with proper guidance while encouraging me to stand on my own. I will forever be grateful for the opportunity you’ve given me to shape up my future career.

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Thank you to my wife, my constant support system over the past few years, for motivating me and encouraging me to pursue my dreams and allowing me to achieve my goals.

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List of Abbreviations

AI – Attraction Index
MMH – Manual Materials Handling
ECG – Electrocardiogram
EMG – Electromyogram
EEG – Electroencephalogram
EOG – Electrooculograms
ERG – Electroretinograms
EDG - Electrodermograms
MCG – Magnetocardiogram
MMG – Magnetomyogram
MEG – Magnetoencephelogram
MSD – Muskuloskeletal Disorder
LED – Light Emitting Diode
GRF – Ground Reaction Force
COP – Centre of Pressure
COPx – Centre of Pressure in x-direction
COPy – Centre of Pressure in y-direction
COPr – Centre of Pressure resultant vector
ROI – Region of Interest
APA – Anticipatory Postural Adjustment
CoM – Centre of Mass

1.0 Bio-instrumentation

Bio-instrumentation is the measurement of living systems with bio-electronic instruments, for the purpose of detecting, recording, processing and transmitting physiological and behavioural information (Wise, 1991). Bio-instrumentation emphasizes common principles and unique problems associated with making measurements in living systems. A theoretical bio-instrument system is a combination of biology, sensors, interface electronics, microcontrollers and computer programming, designed, validated, and synchronized through the application of multiple disciplines including biology, optics, mechanics, mathematics, electronics, and computer science (Enderle, 2006). The typical construction of a bio-instrument contains numerous technical components that are designed to complete unique tasks, including measuring, acquiring, processing, displaying, and storing bio-information of biological systems (Figure 1.1).

1.1 Bio-instrumentation Components

1.1.1 Measurand

The physical quantity or the condition that can be measured using a bio-instrument system is called the measurand (Figure 1.1). A measurand is a collective term for all kinds of signals that can be measured and monitored from a living organism and can be categorized according to the source that generates the signal and the kind of energy they handle. The main measurand types are electrical, magnetic, mechanical, chemical, and bio-hydraulic signals (Singh, 2011).

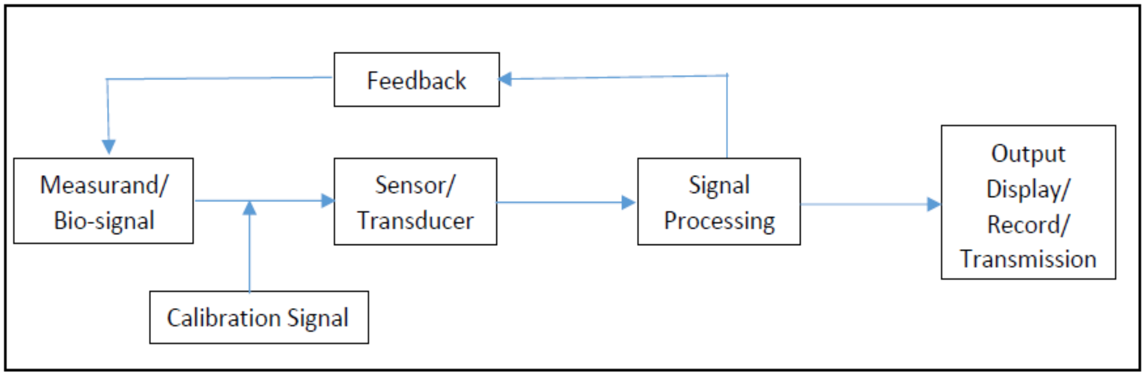

Figure 1. 1 A theoretical bio-instrumentation system using sensors to measure bio-signals with data acquisition, storage and display capabilities, along with calibration and feedback signals.

1.1.1.1 Bio-electric Measurands

Bio-electric signals are the electric signals that have a biological origin, and can be generated by a particular anatomical structure such as a muscle or the brain, or a chemical or a mechanical signal that is converted to an electric signal (Enderle, 2006). These electrical signals are manifested as differences of potential between two points located in some place of the living organism, either inside or on its surface (Valentinuzzi, 2004). Valentinuzzi (2004), describes two types of bio-electrical signals that exist: traditional and non-traditional bio-electrical signals. Traditional bio-electrical signals are the ones that are generated by excitable tissues such as the nerve, skeletal muscle, cardiac muscle and smooth muscles. These signals are gathered with the use of relatively large differential electrodes such as electrocardiogram (ECG), electromyogram (EMG), and electroencephalogram (EEG). On the other hand, the non-traditional bio-electric signals are generated by other tissues such as the eye, or the skin which are capable of producing small differences in potential. To capture bio-electric signals originated from the eye, bio-engineers use electrooculograms (EOGs), and electroretinograms (ERGs), whereas electrodermograms (EDGs) are used to capture electrical signals coming off of skin. Therefore, generally, bio-electric signals provide researchers a proportional reflection of bio-activity happening in a localized area of a living organism.

1.1.1.2 Bio-magnetic Measurands

The term bio-magnetism refers to magnetic fields generated by biological systems. Bio-magnetic sources can be found in electric currents in diamagnetic, paramagnetic and ferromagnetic substances found in the body (Williamson et al, 1983). Diamagnetic substances such as water or water based bio-materials have a relative magnetic permeability that is less than or equal to one, thus resulting in being repelled by the presence of a magnetic field. Paramagnetic substances include most chemical elements and some compounds, of which the relative magnetic permeability is greater than or equal to one, therefore being attracted by external magnetic fields. Ferromagnetic substances such as iron are the strongest type of magnetism, and they intensify the external magnetic fields extremely when present. Just as for the case in bio-electric measurands, bio-magnetic measurands are captured by an array of different bio-instruments that include magnetocardiogram (MCG), magnetomyogram (MMG) and magnetoencephelogram (MEG).

1.1.1.3 Bio-mechanical Measurands

Study of any moving organ, tissue, or systems of tissues with the methods of mechanics is called bio-mechanics. The skeletal voluntary muscles, the involuntary rhythmic contracting myocardium, all smooth muscles covering blood vessels produce bio-mechanical signals that can be measured using various bio-instruments. Within all these bio-mechanical signals, force, length, and angular changes are manifested as basic events (measurements), while tension, acceleration and torque takes place as more complex events (derivations). The electrical signals of skeletal, cardiac and smooth muscles trigger their respective contractions, and thus, they develop force, F, usually accompanied by a change in muscular length, L. The rate at which F and L change over time is an indication of contractility that quantifies velocity of contraction and can be recorded using myograms and cardiomyograms. Human locomotion and gait mechanics is a subject that was pioneered by D.A Winter, and has been explored thoroughly over the years by countless number of researchers (Winter, 1989; Davis et al., 1991; Hreljac, 1995; Medved, 2001). In these studies, special attention is given to kinematic variables, in which bio-mechanical modelling can be used to characterize locomotion and other fundamental behaviours by treating the body as a complex multi-segmental mechanical system. Limbs, trunk, neck, and head are modelled as segments linked with angular movements that generate specific torques.

1.1.1.4 Bio-chemical Measurands

Bio-chemical signals generated from the human body include partial pressures of the gasses in the blood, lungs and other tissues as well as concentrations of metabolites (Singh, 2011). The metabolites are the substances that are necessary for certain metabolic process in the body. These include glucose in the metabolism of sugar, starches, and amino acids in the process of bio-synthesis of protein. Measuring the concentration of various ions inside and in the vicinity of a cell by means of specific ion electrodes is an example of such a signal. The bio-chemical signals produced by humans could depend on various factors such as whether the person is at rest or in motion, ambient temperature and air pressure, and oxygen content of the air. Special sensors are required to monitor these chemical changes especially given the fact that these measures are invasive and at times need to be observed over a long period of time. In return, they provide physicians and researchers with specific characteristics of organs and tissues that are useful in treating patients with various conditions.

1.1.1.5 Bio-hydraulic Measurands

Bio-hydraulics refers to the pressure and flow developed by fluids in certain body cavities. In particular, hemodynamics, a sub category of bio-hydraulics, is of particular interest to the medical professionals, where they study cardiovascular compartments and their moving blood contents. Arterial blood pressure and blood flow are the two main bio-hydraulic events that the researchers are interested in, and bio-instruments such as sphygmomanometers and laser Doppler blood flowmeters are available in today's industry to measure these activities. Bio-hydraulic signals are also measured through one's heartbeat using a stethoscope, where the hydraulic events are being emitted as audible signals.

1.1.2 Sensors

In a bio-instrumentation system, a measurand is detected and converted to an electrical signal with the use of a sensor or a transducer (Figure 1.1). The terms sensor and transducer are used interchangeably in various literature, however it is important to understand the subtle differences between the two terms. Strictly speaking, a sensor just detects the signal under the original type of energy (electrical, mechanical, thermic, magnetic, or chemical), whereas the transducer only transforms the small amount of energy contained in a biological signal into electrical energy (Valentinuzzi, 2004). Thus, a transducer literally 'translates' energy, but it requires a sensor, which is often well immersed in the transducer, making it impossible to separate them. The aim of a sensor is to produce an electronic signal which is proportional to the concentration of a specific chemical or set of chemicals in a biological element (Turner et al., 1987). A sensor is designed to minimize the disturbance to the measured variable and its environment, comply with the requirements of the living system, and to offer maximum clarity to the input signal.

Some transducers' output changes in response to a change in surroundings. These outputs include resistance, capacitance or inductance. The variations in these different outputs can be measured using a Wheatstone bridge circuitry organization such as strain gauges, potentiometers, thermistors, and photoresistors (Valentinuzzi, 2004). The other type of transducers produce a voltage or current in response to a change in environment. Some examples include piezoelectric crystals, linear variable differential transformers, and thermocouples. In both cases, sensors work as analytical tools that combine a bio-signal recognition component off the human body with a physical transducer. The biological sensing elements can be an enzyme, antibody, DNA sequence, or a microorganism. Biosystems within an individual's body selectively cause a bio-chemical reaction, which the transducer converts into a measurable signal, thus providing the means of detecting it. Sensors also have the capability of making use of a neural interface technology to detect nerve and muscle activity. Electrodes that sit on the skin can measure muscle electrical activity, brain electrical activity and eye movement (Tonneson & Withrow, 2006). The electrical signals that the brain uses to control functions of human body have certain measurable qualities including intensity and spectral characteristics, and that is exactly what the sensors detect in order make associations between neural activities and animal behaviors.

1.1.3 Signal Processing

The output from the bio-sensors are analog signals, which are continuous, and require signal processing in order to comprehend and make inferences. These analog signals are usually converted into digital format with the use of an analog to digital (A/D) converter to make the signal storage and analysis more efficient and flexible. With the recent developments in digital hardware and software technology, the digital techniques offer much more powerful, easily implementable complex algorithms that are accurate and not affected by unpredictable variables such as component aging and temperature. At the same time, digital techniques allow the users to change and update design parameters more freely by allowing recurring software modifications.

In bio-medical applications, acquiring a bio-signal directly via a sensor is not sufficient most of the time, as the signals can be buried with many other irrelevant signals (noise), or they might not be detectable from the outset. That is where signal processing with the use of different transformation methods is required to enhance the signal, so that the required information can be obtained. The processing of bio- signals poses some unique challenges. This is mainly due to the complexity of the underlying system, and the need to perform indirect, non-invasive measurements without altering the original signal. There are a multitude of processing methods and algorithms that are currently available to bio-medical engineers, however, in order to be successful, one must have a good understanding of the goal of processing, test conditions and the underlying signal.

In signal processing, bio-signals are categorized into two main classes depending on the signal characteristics. These two classes are continuous signals, which provide information about the signal at any given time, and discrete signals that provide information at a specific point in time. Most bio-signals are continuous, however, most of the current signal processing tools are designed to process discrete signals, thus, bio- engineers tend to transform continuous signals into discrete signals whenever it is possible (Proakis & Manolakis, 1988).

Both continuous and discrete signals can be divided into two main groups called deterministic and stochastic signals depending on their wave patterns (Cohen, 1986). Deterministic signals are the ones that can be described exactly mathematically or graphically. Real world bio-signals are never deterministic as there are always some unknown and unpredictable noise associated with them that render them non-deterministic. However, bio-analysts often model bio-signals as of deterministic waveforms in order to simplify analysis and to make predictions with regards to signals' behaviors. Deterministic signals can be further divided into two categories as periodic and non-periodic signals. Periodic signals have a basic wave form that repeats continuously on the time axis. Sinusoidal signals, the most common type, are often used as the basis to model much more complex periodic signals, in order to simplify their behaviours. On the other hand, most deterministic signals are non-periodic and can be modelled as "almost periodic". A good example is the waveform of an ECG signal that has a variable period length and changes its shape after every heartbeat and thus clearly a non-periodic waveform. Under certain conditions such as a composite ECG consisting of maternal and fetal signal, however, the period length can be almost constant, while continuing an identical wave shape which can be modelled as an "almost periodic" wave form (Kay, 1988).

The other group of signals, stochastic signals, represent sample functions of a stochastic process. This process produces sample functions, the infinite collection of which is called the ensemble. Each sample function differs from the other in its fine details; however, they all share the same distribution probabilities, i.e. random distribution characteristics (Cohen, 1986). Stochastic signals can be categorized into stationary and non-stationary signals depending on their corresponding structures. Stationary stochastic processes are processes whose structures do not change in time, whereas non-stationary processes are time dependant and require complex methods in which they cut the signal durations into small segments, so that they can be considered as stationary.

The bio-signals collected by the sensors are generally represented in the time domain, which characterizes the behavior of the signal with respect to time. However, often in signal processing, these time domain signals are converted into frequency domain in order to simplify the analysis process. There are multiple methods available to transform time domain signals into frequency domain, but the most common transformation principle is called the Fourier transform. Fourier transform is used to convert a signal of any shape into a sum of infinite number of sinusoidal waves which makes the analyzing procedure much simpler (Weitkunat, 1991). The other transform methods include Laplace transform that is used in electronic circuits and control systems, Z transform that is commonly used in digital signal processing, and Wavelet transform that is mainly used in image analysis and data compression (Chui, 1992).

As mentioned earlier, bio-signals are often weak signals contaminated by noise. When a bio-signal is acquired using a transducer from a certain muscle or elsewhere, it not only picks up the electric potential generated by that certain muscle, but also from the surrounding active muscles. Additional noise may also come from other electrical sources surrounding the transducer which can be considered as random errors. Also, faulty instruments as well as procedural errors caused by the researchers that are considered as systematic errors may contaminate the bio-signal furthermore. Therefore, the first step of signal processing is to enhance the signal by "cleaning" the noise without distorting the signal. This is achieved by designing various types of filters (i.e. low-pass, high-pass, stop band, Weiner, matched, etc.) and running the signals through them. Generally, a multi-layered filtering process is sufficient to remove noise in most signals, however there are instances where the signal and noise bandwidth overlap and noise amplitude is enough to seriously corrupt or distort the signal. In such cases, desired response cannot be achieved via traditional filtering (Aunon et al., 1981) and requires a process called averaging. Signal averaging is a technique applied in the time domain that increases the strength of a signal relative to noise that is obscuring it. It sums a set of temporal epochs of the signal together with the superimposed noise, and by averaging them, the signal to noise ratio is increased, allowing the users to remove noise relatively easy.

1.1.4 Output

Once the analog signals are digitized, they can be processed and stored in specialized digital computers or micro-controllers (Tompkins and Webster, 1981), where various types of signal conditioning can be applied.

Once the signal conditioning is completed, the results of the measurement process need to be displayed to the user in a format that is easy and effective to comprehend. Such formats may include numerical and graphical displays that exhibit data continuously or discretely, in a permanent or a temporary manner. These data displaying methods are part of an ever evolving field called data visualization, where the results are dependent on efficient computational methods capable of achieving desired levels of interactivity with the audience (Bajaj, 1998). In addition to displaying the processed digital signals, bio-instruments are also capable of storing data, where they may be stored temporarily for short term analysis, or permanently recorded for future reference. With the development of new information technology in the recent years, data transmission has also been integrated into bio-instruments, where collected data can be transmitted to various other instrumentation systems for further analysis.

There are many other task specific components that are available for bio-instrumentation systems. Some of these components are quite essential for the accurate functioning of bio-instruments, thus require our attention. One such component is called the calibration signal. In almost all bio-instrumentation tasks, the operator is required to perform a calibration step, where a signal with amplitude and frequency is applied to the instrumentation system at the sensor's input. The calibration signal allows the input and output signals to have a meaningful correlation by introducing a reference frame for the system to adjust to. Without such information, the system is incapable of converting the output of an instrument system to a meaningful representation of the measurand.

1.1.5 Feedback Signal

In a simplistic model of a bio-instrument, a measurand is collected from a bio-sensor which then goes through signal processing before being displayed by an output device. This process might hold true for a very short or single burst of physiological signals, however it is often not the case in real life. Almost all of the bio-signals that are analyzed by bio-instruments are continuous and ever changing systems. That is where a control feedback signal is required in order to elicit the measurand, to adjust the sensor and signal conditioner, and to direct the flow of output for display, storage and transmission. Feedback signals accomplish these tasks by collecting physiological data and simulating a response when needed, or by continuously sending back processed data to the measurand to perform real-time analysis on input data.

There also exists a user-feedback system that tests the bio-instrument system's reading and interpretation qualities, where mathematical models are used to improve the quantification process. Many times, the initial model that was used to study bio-systems must be disposed of or modified because its results did not acceptably fit the real situation. Thus it requires the researcher to look back, review, revise, study, search, and experiment again, initiating an endless feedback loop to improve the quality of the bio-instrumentation process.

1.2 Bio-instrumentation potential in occupational biomechanics and psychophysics

Occupational biomechanics is the study of the physical interaction of workers with their tools, machines, and materials so as to enhance the workers' performance while minimizing the risk of musculoskeletal disorders (MSDs) (Chaffin et al., 1999). Analysing the risks of work related MSDs is a challenging task with many obstacles. Dynamic, three dimensional, anatomically complex and electromyography (EMG) driven models are well equipped to simulate industrial manual materials handling tasks, however, they can only be applied in controlled laboratory settings due to the complex nature of instrumentation and data requirements of the current most-widely cited models. (Garg et al, 1982; McGill et al, 1985; Marras et al, 1991, 1995). The multiple risk factors associated with work tasks can be categorized into two groups; physical factors and psychosocial factors. Physical risk factors such as high repetition, awkward posture, excessive force, static work, and vibration affect the workers' musculoskeletal systems directly (Punnett et al, 2004; Nunes et al, 2012), while the psychosocial factors such as work stress, high job demand, monotonous work, and perceived injury risks affect the workers' cognitive stress (Bongers et al, 2002; Punnett & Wegman, 2004). Due to the complexity of these multiple risk factors and their varying psychophysical attributes, use of single factor risk assessment models has proved unconvincing in the past, and thus, a need for a new multi-factorial risk assessment model has been raised (Fernandez & Marley, 2014).

The development of *psychophysics methodology*, a relatively new assessment model for occupational loading, offers an efficient and timely solution to these challenges, where it empirically quantifies subjective tolerance to occupational stress with the use of the dependable variable, *acceptable limit*. Psychophysics offers an opportunity to study worker perception of tasks involving occupational stressors, while gathering bio-mechanical and physiological measurements simultaneously (Fernandez & Marley, 2014).

The workplace is an environment where many adults perform eight plus hours of actions daily. Manual materials handling (MMH) is a frequent, repetitive workplace action that has the potential of causing chronic musculoskeletal injuries among workers (Hagberg et al., 1995). These injuries may stem from behavioral differences, with injury prone workers making unsafe actions during their MMH duties (Marras et al., 2003). An occupational handling task such as baggage handling at an airport (Figure 1.2) can be performed in multiple ways, where the handling techniques could depend on numerous biomechanical, physiological and psychosocial factors that have been shown to have interactively and directly influence MMH musculoskeletal injuries (Ayoub and Dempsey, 1999). With the help of bio-instruments, researchers have been trying to emulate these occupational MMH tasks in human performance laboratories (Figure 1.3) in an attempt to identify the relevant risk factors and to reduce musculoskeletal injury risks at work places.

With respect to the bio-instrumentation basics that were discussed earlier, any instrument setup that follows the typical bio-instrument structure and is capable of collecting valid and reliable data in the occupation field or an occupation experiment could be classified as a relevant occupational bio-instrument. These bio-instruments vary from each other with respect to their functionality, technology, and the conditions in which they operate, and offer a wide range of solutions to the researchers who look to address ergonomic wellbeing of individuals. Bio-instruments such as EMG, transcranial Doppler, dynamometers, motion capture, pressure sensors, and inertial measurement units are quite relevant in biomechanical research and are often used in ergonomic laboratories all over the world. In this thesis however, my aim was to understand and analyze both the perceptual and biomechanical factors that could influence worker behaviours simultaneously, and thus, vision tracking, motion capture, and force platforms were selected as the occupationally pertinent bio-instruments.

Figure 1. 2 A typical occupational work station. In the picture, a baggage handler is seen moving luggages off the conveyer belt. While it may appear to be a simple work task, multiple perceptual and biomechanical factors are directly involved in such work tasks that could potentially dictate the workers' behaviour and safety during their shifts.

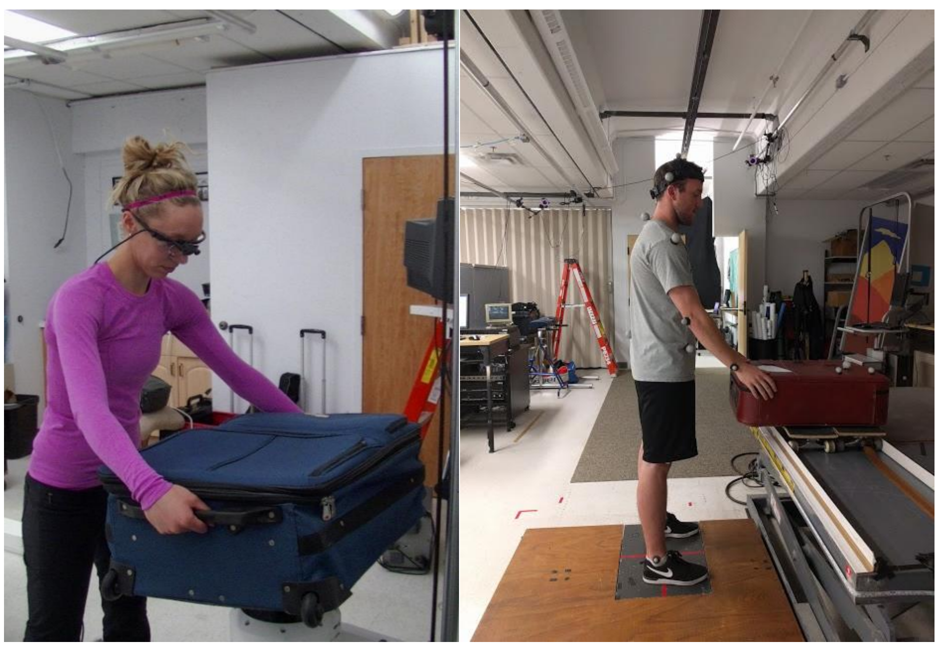

Figure 1. 3 Recreating a suitcase handling work task in the laboratory with different bio-instruments in order to analyze the various factors associated in occupational handling tasks. On the left, the subject is wearing a pair of vision tracking goggles that keeps track of her visual attention during a suitcase handling task. On the right, the participant is equipped with reflective markers on his body in order to track his biomechanical motion using motion capture. He is also standing on a force platform that keeps track of his kinetic profile during the handling task.

1.2.1 Vision Tracking

Vision tracking is a technique where an individual's eye movement is measured so that the researcher knows both where a person is looking at any given moment as well as the sequence in which the person's eyes are shifting from one location to another (Poole & Ball, 2005). Tracking people's eye movements at workplaces may help industrial engineers understand visual and display based factors that could have an impact on workers' cognitive and physical behaviours. Thus, eye-movement recordings can provide an objective source of worker's visual targeting behaviours during work activities, which could potentially be related to the way they complete their work tasks. In order to understand the impact of vision tracking, it is worth exploring the functionalities of eye trackers and how they operate.

Generally, there are two types of eye-tracking techniques: those that measure the position of the eye relative to the head, and those that measure the orientation of the eye in space, or the "point-of-regard" (Young & Seena, 1975). Most commercial eye-tracking systems available today measure point-of-regard by keeping track of multiple ocular features in order to differentiate head movement from eye rotation. Two such features are the corneal-reflection and the pupil centre (Goldberg & Wichansky, 2003; Duchowski, 2007). These video-based eye trackers normally consist of a desktop computer setup with an infrared camera that is either mounted to a table or attached to the head, alongside a display monitor equipped with image processing software to locate and identify the features of the eye used for tracking.

An infrared, corneal reflection eye tracking system relies upon the location of observers' pupils, relative to a small reflected light glint on the surface of the cornea (Young

& Sheena, 1975, Mulligan, 1997). A camera lens (the ‘eye’ camera) is focused upon the observer’s eye that provides pupil movements to the researcher, and a second lens (the ‘scene’ camera) may also optionally be pointed towards the current visual display or scene being viewed in order to study the subject’s visual targeting patterns. In the case of table-mounted eye trackers, a scan converter is frequently used in place of the scene camera. The light enters the retina and a large proportion of it is reflected back, making the pupil appear as a bright, well defined disc, known as the “bright pupil” effect. There exists some cases in which the pupil does not illuminate and results in “dark pupil”, thus eye trackers need to be switched between these modes to find the most robust pupil imaging for a testing environment. The corneal reflection is also generated by the infrared light, appearing as a small, but sharp glint (Poole and Ball, 2005).

Once the image processing software has identified the centre of the pupil and the location of the corneal reflection, the vector between them is measured, and, with further trigonometric calculations, point of regard can be found. Video based eye trackers need to be fine-tuned to each individual subject’s eye movements by a calibration process. The calibration process is achieved by displaying a dot on the screen, and if the eye fixes for longer than a certain threshold time and within a certain area, the system records that pupil-centre/corneal-reflection relationship as corresponding to a specific horizontal and vertical coordinate on the screen. This procedure is repeated over a 9 to 13 point grid-pattern to gain an accurate calibration spread out over the whole screen.

After the calibration of the eye tracker is completed, the researcher can then collect raw vision tracking data by recording the video feed coming in from the “eye” camera and the “scene” camera. Within the raw data, there exists many types of eye-movements that are vital for eye-tracking analysis. *Saccades* are commonly observed when watching an observer's eyes while conducting search tasks. They are small, frequent movements that occur in both eyes at once, range from about 2-10 degrees of visual angle, and are completed in about 10-100 ms (Shebilske & Fisher, 1983). Saccades have rotational velocities of 500-900 degrees/second, resulting in very high acceleration (Carpenter, 1988), and are typically observed about 250 ms following the onset of a visual target. Because of their rapid velocity, there is a suppression of most vision during a saccade to prevent blurring of the perceived visual scene.

Each saccade is followed by a fixation, where the eye has a 250-500 ms interval to process visual information. In an encoding task such as browsing a web page or reading a book, higher fixation frequency on a particular area can be indicative of greater interest in the target, or it can be a sign that the target is complex in some way and more difficult to encode (Jacob & Karn, 2003; Just & Carpenter, 1976). However, during a search task such as looking for a particular tool at a workplace, a higher number of single fixations, or clusters of fixations are often an indication of greater uncertainty in recognising a target item (Jacob & Karn, 2003). Thus differentiating the type of task is extremely important when trying to comprehend eye-tracking data.

Sequences of saccades and fixations form *scanpaths*, which describe the eye's movement from one point to another in a visual targeting activity. During a search task, the most efficient scanpath is the one that is a straight line to a desired target, with relatively short fixation duration at the target (Goldberg & Kotval, 1999). When analysing eye tracking data, scanpaths can be quantitatively analysed by focusing on the derived measures such as the duration, length, regularity, direction, spatial density, and the order of searches which is also known as the transition matrix.

Blink rate and pupil size are two other measurements that eye researchers use as an index of cognitive workload (Poole & Ball, 2005). A lower blink rate could be an indication of higher workload where an individual's visual attention is constantly being engaged, while a higher blink rate may indicate fatigue (Brueneau, Sasse, & McCarthy, 2002; Brookings, Wilson, & Swain, 1996). Larger pupils may also indicate more cognitive effort (Marshall, 2000; Pomplun & Sunkara, 2003), though pupil size and blink rate can be affected by other factors such as the ambient light levels, hence, pupil size, and blink rate are less often used in eye tracking research.

1.2.2 Motion Capture

In order to accurately measure the motion of the body in 3D space, and to obtain a comprehensive overview of the kinematics of various human movements, researchers use a procedure called 3D motion analysis. It has a wide range of applications in numerous industries that include military, entertainment, sports, robotics, bio-mechanics, and ergonomics. While many human motion parameters and events can be measured using a single video camera and 2D motion analysis, 3D motion analysis offers a lot more functionalities in terms of kinematics. Motion capture used in ergonomics studies aim at analyzing injury risks, work postures and bio-mechanics of workers in an industrial setting. High precision motion data coupled with a high fidelity human model, based on anthropometric and ergonomic considerations, may yield valuable data for these kinds of studies, which currently rely mostly on static pose analyses (Bandouch et al., 2008).

Modern motion capture systems generally capture 3D motion data in an automated fashion and in real time. There are four main types of motion capture equipment that are available in the market:

- Video digitising systems – These systems use manual digitising on video pictures, frame by frame, or automated digitising of reflective markers post-video-capture. Video is the only option for 2D analysis, and it is also the only option in situations where attaching markers to the study's participants is not possible (Begg & Palaniswami, 2006).
- Video based reflective marker systems – These systems use reflective markers (passive markers) attached to the participants, where high speed cameras pick up the reflection from the markers. Reflective marker systems automatically capture marker positions and most systems present 3D position-time data of markers in real time or near real time.
- Optoelectronic or active marker systems – These systems use infrared-emitting markers (active markers), which are individually identifiable. Similar to the reflective markers systems, they also automatically capture 3D position-time data of markers in real time.
- Magnetic tracking systems – These systems are quite unique in the sense that they use magnetic field properties along with a set of sensors instead of markers, and returns 6DOF (degrees of freedom) data in real time.

Both reflective and active marker systems are widely used in ergonomics research with reflective marker systems being the preferred choice. Magnetic tracking systems and manual digitising of video images are not very common in today's research. The reflective and active marker systems require markers to be attached to the participants and these markers are either infrared light-emitting diodes (LEDs) for active marker systems, or solid shapes covered with reflective tape for reflective marker systems. The output of these systems are the x,y,z coordinates of each marker as a function of time.

The reflective marker systems use the reflections coming from the markers attached to the participants using multiple video cameras. These high speed video cameras (166 – 500Hz) are equipped with infra-red flash illuminators that surround the camera lens, and sends out pulses of infra-red light which are then reflected back into the lens from the markers. Each camera records a 2D image with the markers appearing as bright dots. Image processing systems isolate the marker dots in the image and record their position (Fisher, 2002). Since they are "passive" markers, each marker trajectory must be identified and tracked. Markers are sometimes hidden from one or more cameras, so the trajectories can be difficult to track. Therefore, it is recommended to have a minimum of 6 cameras for a reflective marker system so that the researcher would not miss out on capturing all the existing markers.

Once the visible markers have been located on the 2D camera images, the coordinates of the centroid of each marker are noted and a series of intersecting rays are mathematically projected from each camera position for each marker. Since the positions and the lens parameters of each camera are known, the rays from the same marker must intersect and the sets of 2D coordinates for each marker can be reconstructed and 3D coordinates of each marker can be calculated (Shao et al., 2001). Finally, markers are assigned to existing trajectories, and any ghost markers (visual noise due to shiny reflective surfaces) are rejected using the image processing software. There are numerous commercially available reflective marker systems in the market, but the most used systems in research are Vicon (Oxford Metrics) and Cortex (Motion Analysis).

Active marker systems also have markers attached to the participant. Markers are light emitting diodes (LEDs) that are powered and cabled and each LED pulses in a set sequence. With only one marker flashing at any one time, the system can automatically identify and track each marker. This is a considerable advantage of active markers systems over reflective marker systems, however, there is also a down side to it. After sampling the first marker, it must sample all other markers before it can sample the first marker again, which means the sample rate reduces as the number of markers increases. The sequential pulsing of active marker systems means marker occlusion and ghosting does not become an issue as in the case with reflective marker systems. In addition, active marker systems are also capable of detecting marker clusters placed together without any errors due to each marker being uniquely identifiable. Active marker systems normally have three cameras mounted in a rigid rectangular housing. Depending on the type of system that is being used, two to three units is sufficient to collect 3D data to great accuracy (Corriveau et al., 2004; Sadeghi et al., 2004). Two most commonly available active marker systems in the market are OptoTrak (Northern Digital, NDI) and CODA (Charnwood Dynamics).

Magnetic tracking devices generate and sense magnetic fields. They are equipped with a transmitter that emits magnetic fields, and a receiver that detects them. Each sensor placed on the participant delivers six degrees of freedom (X, Y, Z, yaw, pitch, roll) information to the processing computer. Also, the sensors do not require to be within the line of sight of the receiver thus it is a significant advantage these systems carry over the other motion capture systems. However, due to their inherent sensitivity to large metallic objects, it becomes a challenge when trying to capture motion data in a big volume of space (Perie et al., 2002). Therefore, magnetic tracking systems are used most often in animation applications and are not usually the preferred tool for ergonomic analysis research and testing.

For reflective and active marker systems, the basic output is 3D marker coordinates moving in time, called "marker trajectories" (Begg & Palaniswami, 2006). These markers create an "exo-skeleton" around the participant which has to be related to an "endo-skeleton" model of the participant (Fisher, 2002). In order to convert the raw marker coordinate data into useful 3D human body kinematics, there are a few steps that need be followed. First, each body segment is defined using at least three external markers. Segments can however, share markers if needed. Then, joint centres are defined using the external marker data and pre-defined templates that creates a virtual skeleton for analysis purposes. Finally, Euler angles are computed at each body segment and joint centre, where local coordinates systems are defined in order to calculate local kinematics with respect to a "parent" body segment. The equations for calculating joint coordinates and segment orientations from external markers are often provided with the motion capture software. Thus, it is the researcher's task to understand and identify the types of kinematic metrics that they need to analyze in a motion capture study, and use the software accordingly to get the desired results.

1.2.3 Force Platforms

In ergonomics research, *kinetics* refers to the forces and moments that are responsible for changing a body's state of motion. Measuring internal muscular forces is not possible without using invasive medical instruments, however, external muscle activity can be measured using force platforms that provide valuable information on joint forces and joint moments during various human activities. Force platforms are commonly used in bio-mechanical lab settings to record and analyze foot-ground reaction forces and moment time histories.

Foot-ground reaction forces (ground reaction forces, GRF) are reaction forces as a result of contact between the foot and the ground, and form an integral part of human movement analysis (Benedetti et al., 1998). There are two types of force platforms that are widely used in research; those based on piezo-electric transducers such as Kistler, and those based on strain-gauge transducers such as AMTI and Bertec (Begg & Palaniswami, 2006). From a research perspective, there is not much difference between the two types as they both essentially measure the same information, only the raw outputs of the systems are different. The output from strain gauge transducer platforms is three orthogonal force components (F_x, F_y, F_z) and three moments (M_x, M_y, M_z), whereas piezo-electric transducer platforms output four vertical forces and four horizontal forces. In software, all systems convert this raw data to the main information of interest in human movement analysis, that is F_x (horizontal medio-lateral force or medial shear component), F_y (horizontal antero-posterior force or AP shear component), F_z (vertical force component), centre of pressure position (COP) and T_z (vertical torque; moment about a vertical axis passing through the COP position).

Force platforms can be very stable devices and the data they produce are critical for kinetic analyses in ergonomic studies. Ergonomic research tasks that involve lifting and handling objects, pushing and pulling loads often have external forces along with gravity acting on the participant's body. Thus, force platforms provide an excellent basis to observe how such external forces could induce different bio-mechanical behaviors in individuals while comparing that data to their normal force profiles. As with a lot of bio-instruments, force platform data can be recorded and analysed using third party software such as LabView and Matlab, where the researchers have the freedom to explore different analysis methods, compared to a limited number of predefined data analytics.

1.2.4 Experimental Software

The bio-instruments that are used in ergonomics research have the typical two main components of experimental bio-instruments, namely hardware system for data collection, transmission and storage, and a software component built mainly for data analysis. Many of the bio-instrument systems commercially available today come with built-in software packages that allow the researchers to analyze and present data in multiple ways. At the same time, there also exists third party software that are capable of analysing various types of bio-data by allowing the researchers to program the data analytics using numerous programming languages. Following is a discussion of the software systems that were used to analyze bio-data obtained from different bio-instruments in my research.

The goal of eye movement measurement and analysis is to gain insight into the viewer's attentive behavior. In vision tracking, the raw data coming in from an eye tracker contains the x, y coordinates of the eye's position with respect to the viewing area. Raw eye movement data for a particular work task may appear informative to a certain extent, however, without further analysis, the raw x, y coordinates do not reveal much information about the subject's visual attention. Although intuitively, and from the knowledge of the task, it is possible to guess where a subject happened to be paying attention in the environment, it is not possible to make any further quantitative inferences about the eye movement data without the use of an eye-tracking software. Within the software, various algorithms are programmed to identify fixations and saccades; the eye movements that best indicate the locations of the subject's visual attention.

Having the eye tracker calibrated prior to data collection allows the recorded x, y coordinates to be accurate and aligned correctly on the scene camera footage. From a signal processing standpoint, the raw x, y coordinate data are used to characterize the eye movement signals in terms of salient eye movements such as saccades and fixations. The analysis task is to locate regions where the x, y coordinates (signal) average changes abruptly indicating the end of a fixation resulting in an onset of a saccade, and then to observe a stationary characteristic indicating the beginning of a new fixation.

Before signal analysis, excessive noise in the eye movement signal must be eliminated. Noise is caused mainly due to the inherent instability of the eye, and the constant blinking. The latter, considered to be a significant nuisance, and generates strong signal perturbation. However, often the eye-trackers are equipped with built-in filters to get rid of blinks, and to return a value of (0, 0) whenever it loses sight of the salient features needed to record eye movements. Noise caused due to various other sources is filtered out by defining an "effective operating range" that is specified in terms of visual angle of the subject. Any signal that falls outside the defined pixel range is therefore left out.

Once the noise is filtered out, next step is identifying saccades and fixations. There are two main approaches to identifying these events; dwell-time fixation detection algorithm and the velocity-based saccade detection (Duchowski, 2007). With the dwell-time fixation detection method, the algorithms first look for a stationary signal that it considers to be the fixation. Then a second criterion is observed where the size of the time window specifying an acceptable range for fixation duration. This classification method suggested by Anliker (1976), determines whether M of N points (x, y coordinates) lie within a certain distance (D) of the mean (μ) of the signal. When the algorithm eventually detects a saccade, the variance of the signal would exceed the threshold D indicating a real positional change. An alternative to the dwell-time fixation detection method is the velocity detection method (Anliker, 1976). In this method, the velocity of the signal is calculated within a sample window and compared to a velocity threshold. If the sampled velocity is smaller than the given threshold, then the sample window is deemed to belong to a fixation signal, otherwise it is a saccade. Yarbus in his research (1967) observed that saccadic velocity is nearly symmetrical (resembles a bell curve), and thus, using this observation a velocity based prediction scheme can be implemented to approximate the arrival time and location of the next fixation. The next fixation location can be approximated as soon as the peak velocity is detected. Measuring elapsed time and distance traveled, and taking into account the direction of the saccade, the prediction scheme essentially mirrors the left half of the velocity profile to calculate the saccade's end point (Duchowski, 2007).

The dwell-time fixation and velocity-based algorithms produce similar results, and both methods can be combined to bolster the analysis by checking for agreement. Once the fixations and saccades have been identified, visual attention results can be quantified and graphically displayed using various plotting and image processing techniques. These functionalities include fixation maps, scan-path visualizations, heat maps, and region of interest (ROI) analyses. Fixation maps are time independent plots that display all the fixations plotted over scene camera images to indicate the subject's visual attention. Durations of these fixations can be user inputted, so that the researchers can isolate specific fixation lengths that they are interested in analyzing. Scan-path visualizations display both the fixations and saccades graphically. These visualizations track the saccadic eye movements using a line graph, while highlighting the fixations using circles of different radii to indicate fixation durations. Heat maps are used to emphasize the strength of fixations using different color schemes that generally demonstrate the areas on a screen where the subject's visual attention was heightened with respect to other areas. Different color schemes such as *grey, jet, hot, hsv, spring* (Matlab) are used to overlay the fixations on top of scene camera images to enhance the visual attention data, while making sure the original image is still visible (Spakov et al., 2007). ROI analyses allow the researchers to focus on a specific area of the visual data screen and analyze all the fixations and saccades that were collected. In a case where multiple clusters of fixations are observed, this method is quite valuable in filtering out any data signals that appear outside of the defined ROI parameters. Matlab (Mathworks), a multi paradigm numerical computing environment and a fourth generation programming language allows eye tracking researchers to perform all the aforementioned graphical analyses and image processing with its built-in tool boxes and graphical user interfaces, designed specifically to simplify eye-tracking analyses. In this thesis, all the bio-data collected via various bio-instruments were analysed using Matlab as it is the common practice in basic and applied science today.

The data collected from motion capture and force platforms are used to calculate kinematic and kinetic metrics using programmable software such as C, C++, and Matlab. In the case of Motion capture systems, recorded 3D positions (x, y, z) of each body segment and joints are combined to produce a template that is a representation of the subject's skeleton. Using these 3D position data in a vector analysis software such as Matlab, the researchers are then able to calculate the kinematic measures such as displacement, velocity, acceleration, angular motion, and particle trajectories. Similarly, the force platforms record the forces and torques that act upon a subject during a work task. With the use of Matlab, researchers can calculate the kinetic measures such as ground reaction forces, centre of pressure, forces acting on different body segments as well as resultant forces and torques. By measuring kinetics and kinematics data simultaneously, joint forces and moments can be calculated via a mathematical process known as inverse dynamics (Begg & Palaniswami, 2006). Inverse dynamics is the process of computing the net joint forces, joint moments and joint power, and the calculations require kinematics data (positions and orientations of joints and segments as well as their linear and angular velocities and accelerations), ground reaction force data and anthropometric data. Joint moments are the result of forces produced by muscles and ligaments acting at a distance from the joint centre. Joint power is the net rate of generating or absorbing energy by all the muscles crossing a joint and is calculated as the product of the joint moment and the angular velocity between the two segments defining the joint (Winter, 1990; Meglan & Todd, 1994). Joint forces, moments and power during ergonomic activities are critical to the understanding of injury prevention and proper work techniques. Thus, using the appropriate software to perform the necessary bio-mechanical analyses becomes a vital component in ergonomic research.

The field of bio-instrumentation is on a continuous climb with countless technical advancements being made resulting in affordable, high functioning instruments with incredible detection and computing powers. However, there still seems to be a missing link when it comes to ergonomic experimental software development. A key word search of

"Ergonomics" and "Matlab" in the Pubmed biomedical database resulted in 30 articles, while the 'Web of Science' database yielded 18 articles for the exact search as of January of 2018, suggesting the lack of experimental software in ergonomics and the need for further research in this field. Ergonomic researchers and biomechanists continue to prefer using default software systems that bio-instrument manufactures produce over custom built experimental software. Even though these default software offer numerous data analysis methods that are well known, with high precision, they all have limitations that bind the researchers to a set number of analysis techniques and prevents them from further expanding their research into higher order analyses. Custom experimental software on the other hand, offer all the analysis methods that the default software can offer, and allows the luxury of adding in numerous high level analysis methods as well as novel analysis principles that the researcher may want to experiment with. Numerical analysis software such as Matlab, Labview and Analytica are capable of providing high-level numerical analysis methods by either using already existing functionalities, where the user can combine multiple built-in functions to create a high structured analysis program, or design a completely new analysis program from ground up. The result is a well-structured high level analysis program offering much more than the basic break down of data, and thought provoking results which may induce even deeper discussions with regards to data analysis. Therefore, it is imperative to explore the potential impact custom experimental analysis software may have on ergonomic research and it requires further attention from biomechanical and ergonomic researchers.

The purpose of my thesis is to begin the design and validation of a 21st century occupational psychophysics toolbox that pairs off the shelf bio-instrumentation hardware components, namely vision tracking, motion capture, and force platforms with custom Matlab based experimental software capable of image processing, assessment of full body kinematics and analysis of ground reaction force kinetics to comprehensively study perception action coupling from select occupational tasks. It is hypothesised that unique (and explanatory) characteristics of perception-action coupling in occupational behaviour would be revealed through the logical experimental combination of conventional human movement bio-instrumentation, custom scientific data analysis software, and ecologically valid experimentally occupational tasks.

1.3 Summary

Bio-instrumentation is the development of technologies for the measurement and manipulation of parameters within biological systems, focusing on the application of engineering tools for scientific discovery and for the diagnosis and treatment of disease. Though the bio-instruments may vary with their components and functionalities according to the biological system that they are dealing with, in general they all have a common instrumental set up comprised of sensors, calibration signals, signal processing unit, feedback signals, and an output display and transmission feature. In the fields of ergonomics and biomechanics, the use of bio-instrumentation for the purpose of analysing work related MSDs for injury prevention has become the norm. Subsequently, the relatively new assessment model, occupational psychophysics, has allowed the use of bio-instruments to be more efficient by addressing both the perceptual and physiological challenges that arise at work places.

In this thesis, I have made use of three commonly used bio-instruments, vision-tracking, motion capture, and force platforms, and have coupled them with Matlab based experimental programming in an attempt to identify the visual, kinematic and kinetic concepts associated with occupational lifting tasks.

1.4 Outline

In Studies 1 and 2, I examined visual attention preceding a manual material handling task, and associated visual attention with explicit pre-handling arousal, implicit directional cues for action, and subsequent handling strategies. My goal was to differentiate how negative and positive motivational states along with implicit visual cues could influence MMH perceptions and actions that may lead to work related musculoskeletal injuries. I used a pair of vision tracking goggles (ASL) to capture individual's visual attention data, and combined it with custom Matlab software to process, analyse and to visually represent the results.

In Study 3, I observed the perceived horizontal affordance distance of workers during an MMH task, and studied whether the affordance distances could be modified using implicit directional cues. I performed a conventional motion capture kinematic assessment and a postural kinetic evaluation by making use of two commonly used bio-instruments in the industry, a high speed motion capture system and a force-platform. By combining the two bio-instruments with another custom matlab software capable of modelling handling behaviors into mathematical equations, I was able to discriminate handling behaviours by visual cue type for work place risk assessment.

2.0 Quantifying Visual Attention for a Manual Materials Handling Task

2.1 Introduction

Visual attention is one of the key information contributors in the process of carrying out the human activities of everyday life. Visual attention has four basic components; (i) selection of the region of interest in the visual field, (ii) selection of feature dimensions and values of interest in that region of interest, (iii) control of information flow through the network of neurons that constitutes the visual system, and (iv) frequency and order of shifting from one region of interest to the next (Tsotsos et al., 1995). It is noteworthy that the first two components of visual attention occur prior to any subsequent action, suggesting that predictive visual attention precedes actions in everyday activities, as previously observed in natural behaviours and tasks such as walking (Marigold and Patla, 2008) and reaching (deBruin et al., 2014). The direction of visual attention is typically defined by two behaviours of the eyes, specifically fixations, (where the visual gaze is maintained on a single location), and saccades, (movements of the eyes between two fixation points) (Duebel & Schneider, 1996). Measuring fixation patterns and saccadic movements provides us with a means of studying visual attention, and associating those behaviors with upcoming actions (Yarbus 1967; Hayhoe & Ballard, 2005). Measures of real-world visual attention have been widely used in sports science, including table tennis, golf, baseball, and darts, to examine the perception-action coupling, accuracy, efficiency, and psychophysical status of athletes (Vickers, 1992, 1996, 1997). Numerous experimental visual attention studies have used screen-based eye-tracking as a means to substantiate possible relationships between visual attention and everyday human actions (see Nguyen et al., 2016 for a review), and the technological advances continue to open new environments for investigation (Hayhoe, 2018).

The workplace is an environment where many adults perform eight plus hours of activities daily. Manual materials handling is a frequent, repetitive workplace activity that has chronic potential for causing musculoskeletal injuries amongst workers (Hagberg et al., 1995). These injuries may stem in part from behavioral differences, with injury prone workers making specific unsafe actions during their manual materials handling duties (Marras et al., 2000). Motion and principal component analyses identify the kinematic evidence of these injury-risk behaviors (Marras et al., 1995; Wrigley et al., 2005), but less is known about perceptual differences that may precede (and possibly predict) these different action patterns (Bigos et al., 1991; Mullen, 2004). By identifying and quantifying preceding visual attention patterns in the workplace, we might be able to predict personal handling behaviours, and thus risk of work-related musculoskeletal disorder.

A manual materials handling task can be performed in multiple ways, where the handling techniques could depend on numerous factors. Assuming the workers are physically healthy and are familiar with their work tasks, their lifting patterns may be determined by the visual attention patterns and the pre-lift instructions. For example, workers fixated on an upstream object on an assembly line might move and lift differently than workers attending to the decreasing space between them and the same object. With the use of proper research and analysis methods, we might be able to predict differences in handling techniques and work-related musculoskeletal loading by investigating spatiotemporal characteristics of worker's pre-lift visual attention patterns.

In this two-part experiment, our goal was to examine visual attention preceding a manual material handling task, and to associate visual attention with explicit pre-handling arousal (mental state), implicit directional cues for action (physical context), and subsequent handling strategies (behaviour). In Study 1, participants were primed with one of two handling task arousal states, then asked to grasp and move a suitcase while their visual attention and handling behaviour were recorded. In Study 2, participants performed the same task with the same primes plus additional visual cues proposed to affect handling behaviour. Previous research has shown that visual cues do effect reaction times, while automatically triggering orienting of attention (Posner, 1980; Tipples, 2002). Although the influence of explicit and implicit cues on visual attention is well known, their effectiveness in moderating manual materials handling tasks and work-related activities requires further research. We hypothesized that pre-handling explicit contexts would encourage participants to perform the manual materials handling activity with different perceptual and behavioral strategies (Study 1), and that implicit visual cueing would have the capability to influence the effects of the context, influencing participants to handle the loads in differing manner (Study 2). We investigated the relationship between visual attention and manual material handling actions, with the goal of preventing injurious occupational behaviours.

2.2 Methods

2.2.1 Study 1

2.2.1.1 Experiment

Thirty-one university undergraduates (21.5 ± 4.5 years old, 17 female) with normal or corrected-to-normal vision were recruited. A horizontally oriented suitcase (72 x 45 x

25cm) was securely fastened and fully supported on a LIDO WorkSet II dynamometer (Loredan Inc, MA, USA; Figure 2.1), and was initially concealed under an eye tracker calibration board prior to the work task. Participants' heights were measured and the suitcase was vertically adjusted so its vertical centre was at 53% of each participant's height. Participants were instructed to position their feet inside a 40cm square that was 25 cm posterior to the centre of the suitcase. A pair of Mobile Eye - XG vision tracking goggles (Applied Science Laboratories, MA, USA) were worn by each participant. The goggles' reflector lens and vision camera were each adjusted to capture eye movement data that were within each individual's para-central vision. Prior to the work task, each participant took part in a calibration exercise of the goggles, where they stood in front of a horizontally-oriented calibration board with nine markers placed on it, arranged in a 3 x 3 matrix (79 x 62cm). Participants were asked to focus their gaze on each of the markers for a few seconds, while the vision-tracking software collected and calibrated the data from the goggles to make sure that the right pupil was aligned with each marker.

Figure 2. 1 Suitcase orientation during the handling task. The suitcase is placed on a LIDO dynamometer while the subject is also equipped with vision tracking goggles.

2.2.1.2 Protocol

Subjects were randomly assigned into one of two groups, either WINNING (n = 15) or WORKING (n = 16)], and were read a script that explicitly established their group's pre-handling context. The WINNING script informed the participants that they had just won a free cruise trip to San Diego, California, and were required to grasp a single loaded suitcase in front of them to leave for their free vacation. The WORKING script informed the subjects that they had been working at an international airport as a luggage handler for an extended period of time, with long hours plus low autonomy and fixed compensation, in a position that required the workers to repetitively handle suitcases as part of their daily work activities. Both scripts are available in Appendix A. After reading the script, investigators gave participants a short count-down then revealed the suitcase by rapidly hoisting the calibration board. Participants were then given a 10 s 'gazing period' where they had an opportunity to visually examine the suitcase before handling it. These 10 s were when the eye behaviour was recorded.

2.2.2 Study 2

2.2.2.1 Experiment

Fifty eight university undergraduates (21.3 ± 4.4 years old, 43 female) with normal or corrected-to-normal vision were recruited, ten of them having also participated in Study 1,. The protocol for Study 2 was similar to Study 1, with the addition of implicit directional visual cues (bright yellow triangles, 165 cm^2 in viewable surface area) placed on the target suitcase for each trial.

2.2.2.2 Protocol

Participants were randomly divided into two groups [WINNING (n = 29) and WORKING (n = 29)], and were read the corresponding WINNING or WORKING script from Study 1. The implicit visual cues were arranged in two different orientations such that they provided either a CONVENTIONAL cue or a COUNTER cue to the typical grasping behaviours observed in Study 1. Orientation 1, consisting of two triangles positioned close to the centre of the suitcase and pointing to both lateral ends of the suitcase was the CONVENTIONAL cue to the WORKING script and COUNTER cue to the WINNING script, while Orientation 2 (a single triangle positioned near the centre of the suitcase and pointing to the front handle) was the CONVENTIONAL cue for the WINNING script and the COUNTER cue for the WORKING script.

2.3 Analysis

All the activities in both experiments were captured using the scene camera of the eye-tracker along with the corresponding vision data (pupil coordinates) for analysis.

For both experiments, two alternative suitcase grasp types were identified: unimanual handling from the front handle or bimanual handling with one hand on the front handle and the other on either side handle or side, or with opposite hands on each of the right and left side handles (or sides) of the suitcase. Frequency of grasp types were compared between groups to detect possible associations between handling techniques, preceding perceptions, and implicit visual cues.

The vision tracking data collected from the eye-tracker were saved as Microsoft Excel files, and contained the following information: Frame number, x and y coordinates of the master spot in eye image pixels, x and y coordinates of the pupil center in eye image pixels, pupil radius in eye image pixels, eye direction with respect to the scene image in scene image pixels, mouse cursor position with respect to the scene image in scene image pixels. From these data, we were interested in the master spot coordinates, which indicated the visual targeting areas of individuals in the form of the eye-image pixels. Eye images had a resolution of 768 pixels horizontally and 576 pixels vertically.

The first step of the vision tracking data analysis was noise filtering, where all unavailable frames (resolution pixels greater than 768 horizontally and/or 576 vertically) were removed from the collected data files. This was done by programing a Matlab function (EyeFilter), in which the program explicitly searched for any error coordinates (-2000 or coordinates outside of 768 x 576), and then filtered them out by deleting the corresponding data that were associated with those frames.

The vision tracking data were then analysed using a Matlab based eye-tracking software called ‘EyeMMV’ (Krassanakis et al., 2013). EyeMMV is a freely available eye-tracker data analysis software that is capable of analysing vision tracking data and produces various types of visually representative results in the form of heat maps, fixation maps, and scan-path visualizations. When analyzing heat map results, it is important to keep in mind that there are two factors that affect heat map results: the number of fixations and the duration of those fixations. In our analysis, the heat maps are a product of these two factors, where the higher the number of fixations and/or the greater the duration of each fixation, the more intense the color of those resulting fixation areas. The data representation scheme is a colour spectrum map, where the highest intensity corresponds to the color red. Some coding modifications were added to the software in order to make sure that it was compatible with the eye-tracker while providing us with added benefits. These modifications included: (i) capability of handling Excel data files as input by adding in a data file conversion subroutine, (ii) adjustments to the heat-map and fixation map generator subroutines to accommodate the eye-tracker specific pixel resolutions and coordinate types, and (iii) *save* functionality to all the functions that were available, so that the processed data and images can be stored for future use (Appendix B).

In addition to all the analysis methods that were readily available through EyeMMV, we've also developed a new functionality called Attraction Index (AI). The AI is a number that was calculated in order to compare the visual attention on two or more fixation points. The AI provides a quantified representation of the visual targeting results compared to the traditional way of visually representing eye-tracking results. For the purpose of current study, the AI identified the strength of visual attention amongst participants during the suitcase handling task. It took into account three main factors; number of fixations (number), duration of each fixation (duration), and the relative distance (distance) of each fixation from one of the three handles of the suitcase, such that

$$Attraction\ Index = \frac{(\text{number x duration})}{\text{distance}}$$

AI may provide a strong and simple indicator of the pre-movement visual attention. The AI function was programmed in Matlab to produce an AI-map that would indicate the fixation points of individuals with respect to the three handle points.

2.4 Results

2.4.1 Study 1

There was a clear distinction between the two groups for their handling motivation and their subsequent handling techniques. The WINNING group had significantly increased handling motivation that the WORKING group (Figure 2.2), based on their physical response (pointing to a number on the response line) to the question 'After just hearing your instructions and getting into your role, how are you feeling right now about handling this specific suitcase?' where the response line ran from -5 (anchored with text 'VERY BAD') on the left to +5 (anchored with text 'VERY GOOD) on the right, in equal increments of 1 and with additional anchor text of 'SOMEWHAT BAD' between -3 and -2, 'NEUTRAL' at 0, and 'SOMEWHAT GOOD' between + 2 and +3. The WINNING group handled the suitcase only from the *front* handle on 73.3 % of trials, thus indicating their preference for unimanual handling over bimanual handling. The WORKING group's preferred handling technique was *front and side* grasping *(*50% of the trials). When we collapsed these results into unimanual handling and bimanual handling (including both sides and front and side grasps), the WORKING group's preferred handling technique was bimanual (68.8% for WORKING; Figure 2.3). A two-way log-linear analysis was used to produce a final statistical model that retained all effects. The likelihood ratio of this model was [$X^2(0) = 0$, $p = 1$]. This indicated that the highest-order interaction (the group by handling interaction) was significant [$X^2(2) = 20.305$, $p < .001$]. To interpret this interaction, a chi-square test was performed comparing WORKING and WINNING groups. There was a significant interaction between group and handling, selected, [$X^2(1) = 5.490$, $p = .032$]. The odds ratio showed that the odds of selecting a unimanual grasp were

6.05 times higher with the WINNING than the WORKING script. Therefore, the analysis suggested that bimanual handling was typically selected in the WORKING context, whereas unimanual handling was typically selected with the WINNING script.

The vision tracking results were studied by comparing the heat maps of the two groups. This analysis revealed that, for the WINNING group, the Attraction Index (AI) was highest for the front handle (extending to the central region) of the suitcase, compared to the WORKING group's fixations, which were more distributed around the suitcase, but falling predominantly on the left (direction of movement) side. These results are summarized in Figure 2.4, and exemplar heat maps are shown in Figures 2.5a and 2.5b.

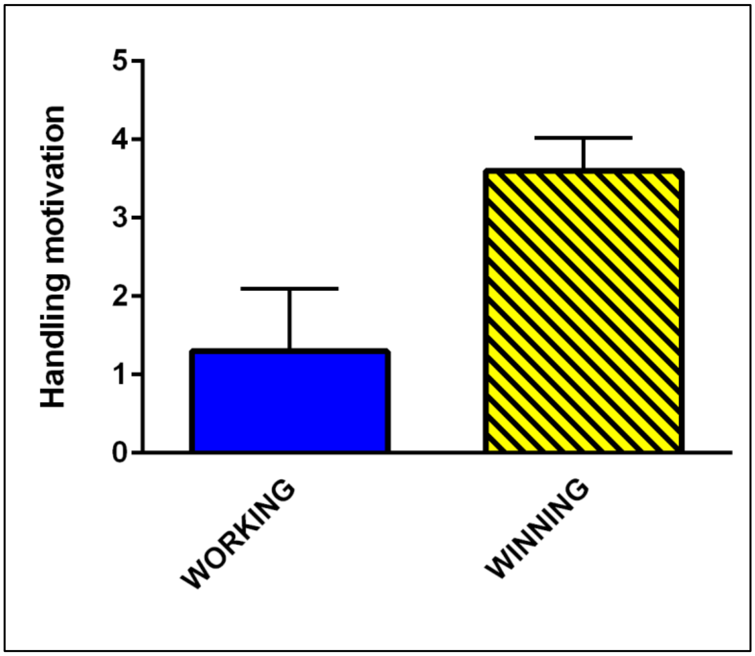

Figure 2. 2 Handling motivation results. Motivation was recorded on a subjective scale ranging from -5 (feeling VERY BAD about handling this case) to +5 (feeling VERY GOOD about handling this case). WINNING group had a higher motivation rating than the WORKING group.

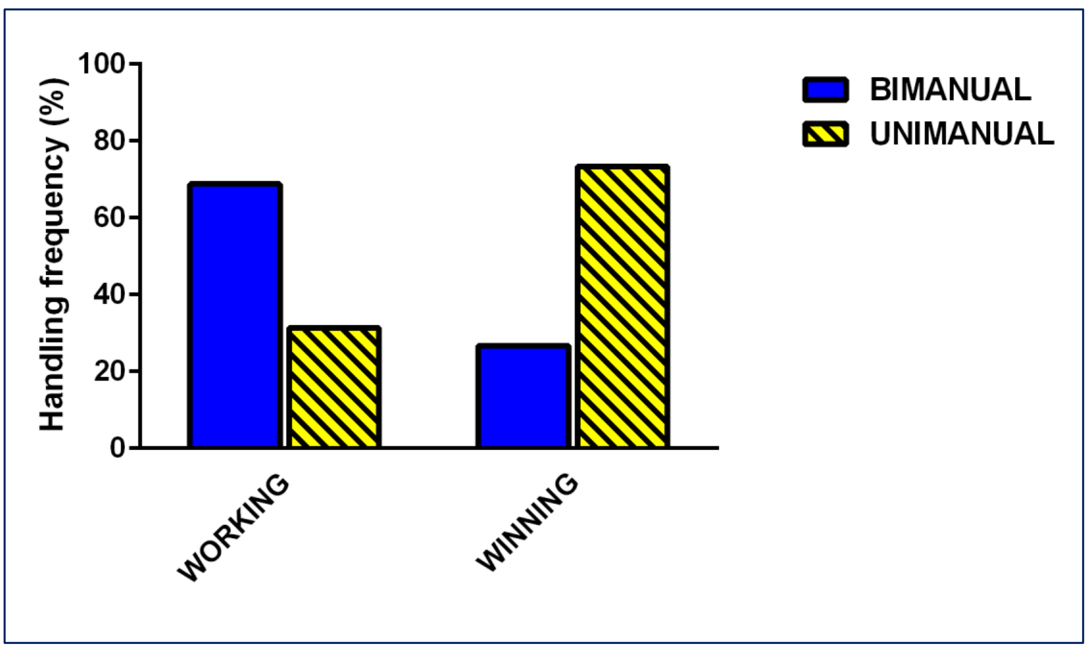

Figure 2. 3 Handling frequency results. WORKING group's preferred a bimanual handling technique while the WINNING group preferred a unimanual handling method.

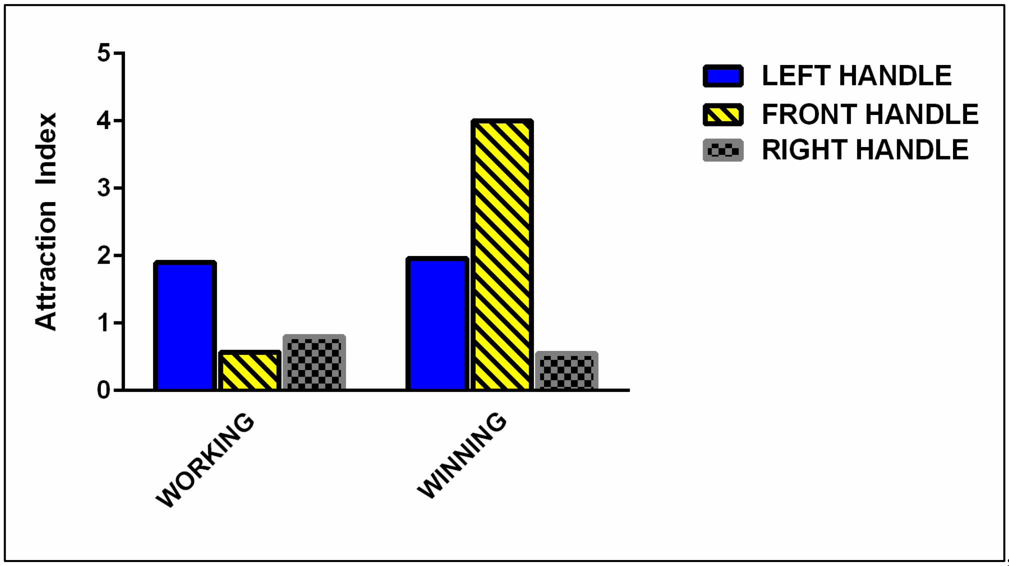

Figure 2. 4 Attraction Index (AI) results. WORKING group's highest AI was for the left handle, while the WINNING group's highest AI was for the front handle indicating their preferred unimanual handling technique.

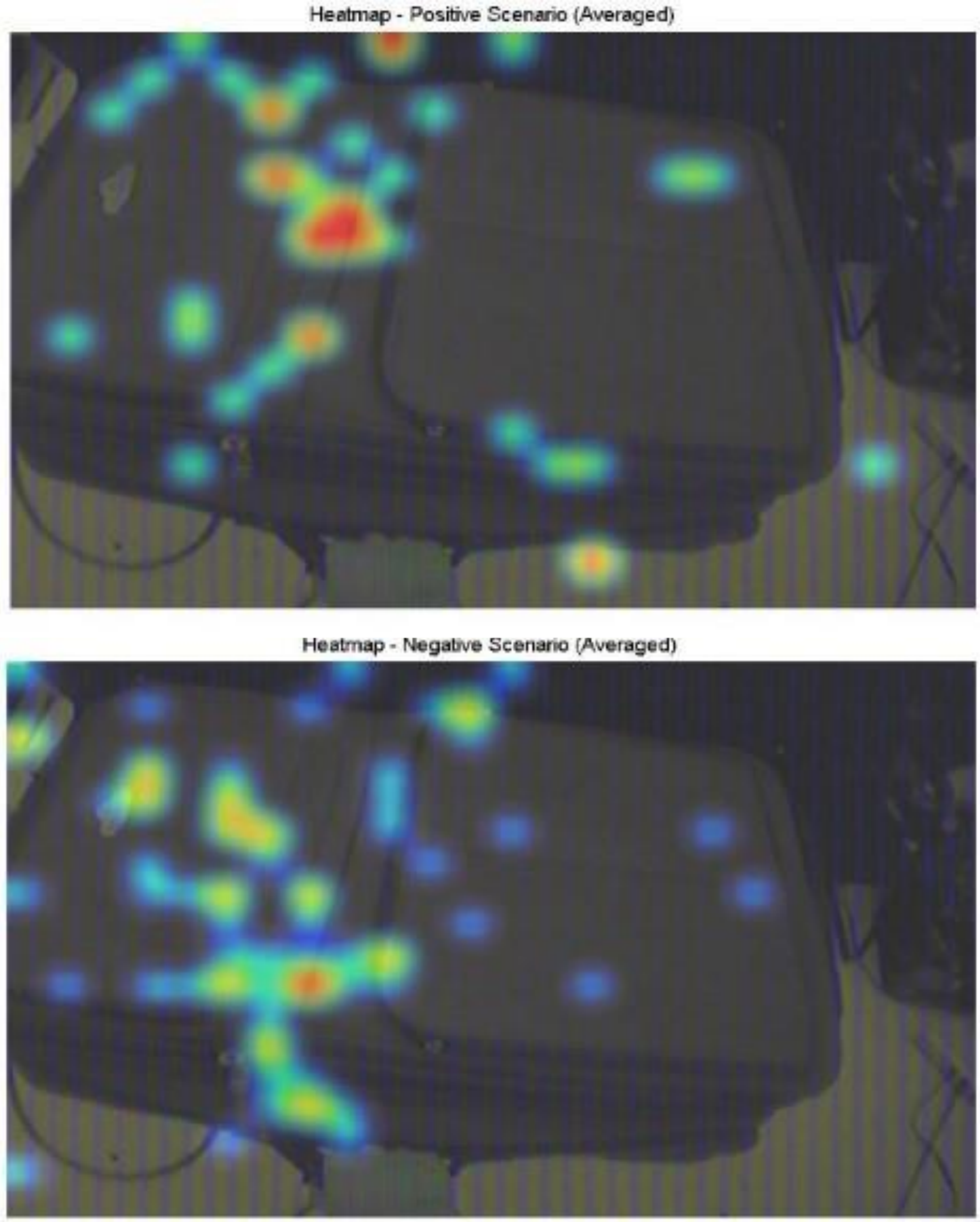

Figure 2. 5 Heat map results. 2.5a (top) shows that for the WINNING group a concentrated fixation was visible at the centre of the suitcase. 2.5b (bottom) indicates a cluster of smaller fixations spread around the left hand side of the suitcase.

2.4.2 Study 2

The WORKING group continued to display the highest percentage of bimanual handling (76% of total trials), while the WINNING group's preferred method of handling was from the front handle (65% of total trials; Figure 2.6). Interestingly, CONVENTIONAL cues strengthened the favoured behaviour of bimanual handling amongst the WORKING group (100% of WORKING-CONVENTIONAL trials) while members of the WINNING group seemed impervious to the cueing. A three-way loglinear analysis was used to produce a final model that retained all effects. The likelihood ratio of this model was [$X^2(0) = 0$, $p = 1$]. This indicated that the highest-order interaction (the *group* by *cue* by *handling* interaction) was significant, [$X^2(2) = 3.961$, $p < .047$]. Separate chi-square tests were performed for WORKING and WINNING scripts. For the WORKING script, there was a significant association between the type of cue and whether a unimanual or bimanual grasp was selected, [$X^2(1) = 5.639$, $p = .026$]. This interaction was caused by a mixture of unimanual and bimanual grasps with a COUNTER cue but only bimanual grasps with a CONVENTIONAL cue. For the WINNING script, the association between the type of cue and whether a unimanual or bimanual grasp was selected was not significant, [$X^2(1) = 0.338$, p .683]. Therefore, the analysis suggested that a unimanual grasp was typically selected with the WINNING script regardless of the type of cue.

The visual cues for Study 2 were introduced for the purpose of studying any possible superseding effect implicit directional visual cueing may have on typical manual materials handling behaviours in the work place. As we observed from our results in Study 1, the WINNING group's preferred handling method was from the front handle of the suitcase, whereas the WORKING group preferred handling the suitcase with two hands. In

Study 2, we strategically placed visual counter cues on the suitcase for each group, which we predicted would prompt opposite handling results as to what we observed in Study 1. Thus, a pair of arrow cues pointed at the two side handles were placed on the suitcase for the WINNING group, while a single arrow cue pointed towards the front handle was placed on the suitcase for the WORKING group. The vision tracking results from Study 2 demonstrated distinct fixation patterns of the participants during their gaze period (Figure 2.7). The WINNING-COUNTER cue group had a concentrated fixation directed at the front handle, despite the paired counter-cues pointing towards the sides (Figure 2.7a). The WORKING-COUNTER group's vision data looked a bit more scattered, however, there was one particular concentrated heat signature directed right at the counter-cue arrow (Figure 2.7b).

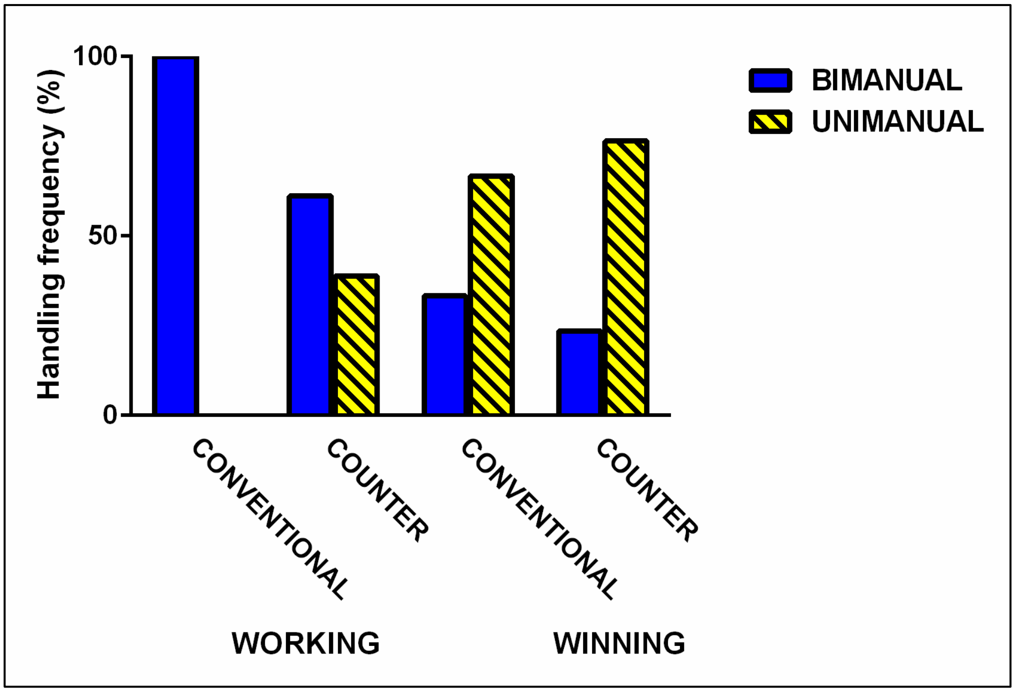

Figure 2. 6 Handling results from study 2 indicating the impact of counter and conventional visual cueing on handling techniques. Counter cues had a greater impact on the WORKING group by encouraging participants to attempt unimanual handling compared to the conventional cues.

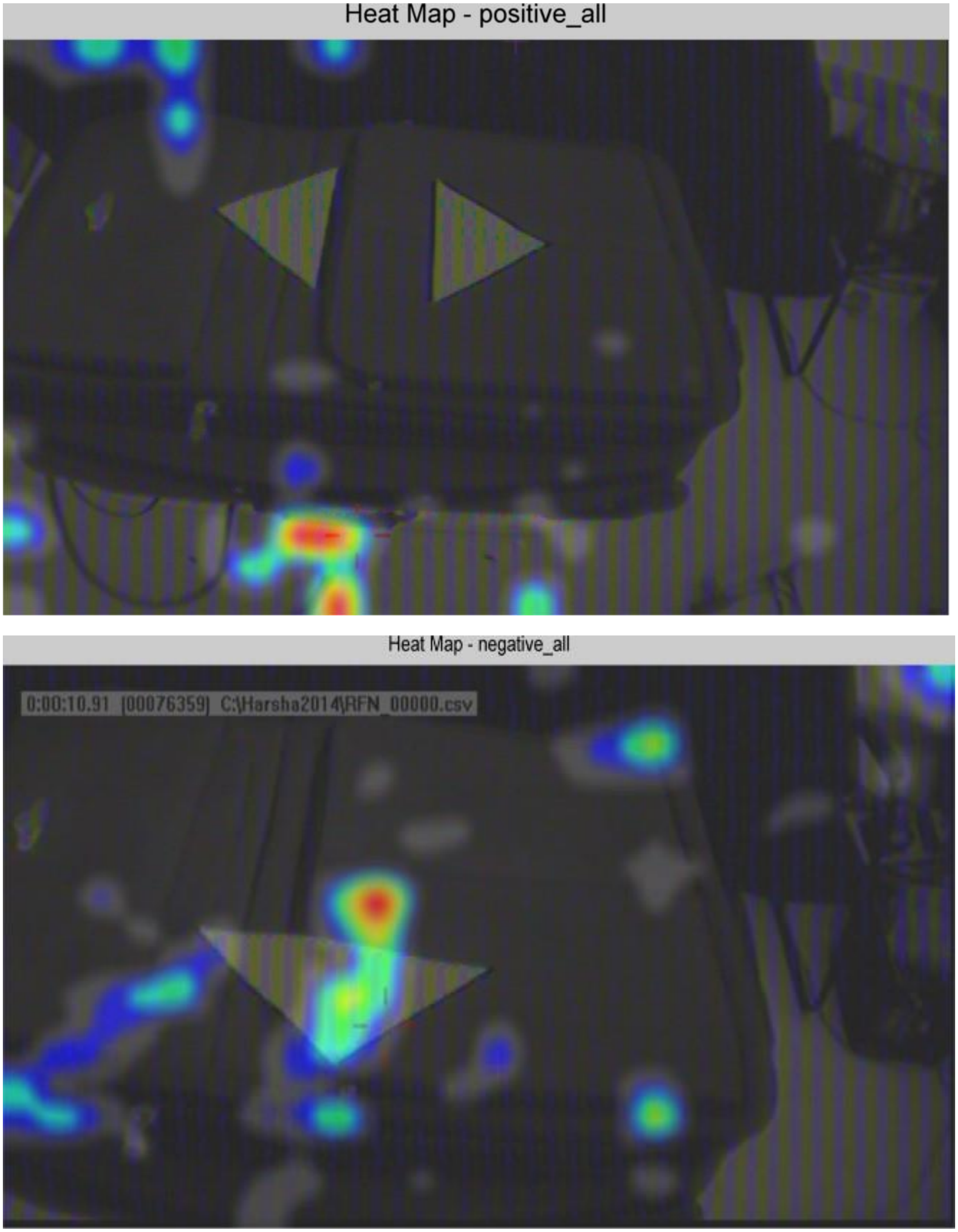

Figure 2. 7 Heat map results from study 2. 2.7a (top) shows a concentrated fixation at the front handle of the suitcase for the WINNING group with counter cues. 2.7b (bottom) shows a more scattered fixation pattern with one concentrated fixation on the counter visual cue for the WORKING group.

2.5 Discussion

The introduction of implicit directional visual cues aligned in either conventional or counter directions to preferred handling behaviours provided us with an opportunity to study how visual attention to cues may encourage certain manual materials handling techniques. Our results suggest that visual cues have an impact on the handling behaviours of individuals. The percentage of unimanual handling remained the same for the WINNING group when the cues were introduced, but the WORKING group's bimanual preference increased significantly with logically consistent cues. It is possible that consistent cues provided assurance to the participants that they were performing the handling motion the correct way. The counter visual cues for both groups did generally encourage more opposite handling techniques as to conventions observed in Study 1, but it was not a significant change. Further research focusing on the modifying effects of cues may prove valuable in safely shaping work-related behaviours in actual workplaces. Following on our experiment, it might be possible to 'nudge' workers to use safer handling techniques, namely bimanual handling, by placing or projecting logically consistent visual cues on to the item to be lifted.

By studying individuals' visual attention prior to a manual materials handling activity, we hoped to gain more insight in to possible relationships that might exist between perception and manual material handling techniques, as previous researchers have done for sports (Vickers, 2009). Vision tracking results from Study 2 clearly indicated a concentrated visual attention towards the front handle for the WINNING perception group. The WORKING group's heat signatures were concentrated on the implicit visual cue, which supports our suggestion that visual cues could have a formative impact on occupational visual attention and manual materials handling behaviour. The concept of

Attraction Index (AI) quantified the strength of each eye-fixation with respect to a certain target location was derived. AI may be a useful tool when the visual targeting results are not isolated enough to draw conclusions just through qualitative analysis. The WINNING perception group had the highest AI for the front handle, which confirmed previous findings of visual attention having an impact on spatial object manipulation. It also indicated that for the WORKING group, the side handles (left and right) had higher AI values compared to the front handle. Eye tracking may provide an excellent indicator of visual and cognitive attention, and thus might be used as a tool to confirm the modification of workers' visual attention, to subsequently modify manual materials handling behaviour to ultimately reduce injuries at work.

2.6 Conclusion

The purpose of this study was to examine visual attention preceding a MMH task, and to associate visual attention with explicit pre-handling motivations, implicit directional cues for action (physical context), and subsequent handling strategies (behaviour). I've found that MMH behaviours were influenced by state conditions. Specifically, purpose and motivation to handle a load changed preferred grasping behaviours (and subsequently musculoskeletal load). Visual cues with directional sense seem to have potential to modify grasping behaviour, even without specific instructions to attend to cues.

3.0 System Engineering Analysis of a Manual Materials Handling Task

3.1 Introduction

Manual materials handling (MMH) tasks are present in many service and industrial workplaces today, and are a primary source of disabling musculoskeletal disorders (MSDs) (Ayoub & Mital, 1989; Dempsey, 1998). MMH tasks such as lifting, lowering, pushing, pulling, holding and carrying pose physical stresses to the worker that may accumulate into stresses on the musculoskeletal and cardiovascular systems. If the stresses placed on these systems exceed the capacity, the potential results are discomfort, fatigue or injury. Biomechanical, physiological and psychophysical factors have been shown by previous researchers to directly and interactively influence MMH musculoskeletal injuries (Ayoub & Dempsey, 1999; Dempsey, 2010; Plamondon et al., 2010). Controlling these factors can reduce musculoskeletal injury risks, but controls need to be capable of consistently positively shaping behaviours for the majority of workers. Visual cueing has been shown to have a direct influence on individuals' orienting of visual attention, subsequently modifying general behaviours (Posner & Cohen, 1984; Nevo et al., 2010), and thus may be useful in modifying workers' perception of safe affordance and subsequent behaviours during MMH tasks.

Motion capture kinematic analysis is often used by researchers to identify detailed biomechanics and work techniques associated with MMH tasks. Motion capture systems record biomechanical movements at high frame rates then reconstruct the collected images into coordinate based biomechanical models representing limbs and joints of the subjects. The camera system is calibrated prior to data collection, where a virtual 3D space representing the experimental space is set to collect motion data. The cameras capture 2D images of the reflective markers that are placed on the subjects, which are later reconstructed into 3D positional vectors with the help of the motion capture software. The software compiles all the positional vectors in a continuous time sequence, which can then be played back in the aforementioned virtual space. Once the positional data are filtered, they can be analyzed using different numerical methods to calculate corresponding linear and angular kinematics. The majority of previous MMH research has focused on using kinematics for identifying the differences in handling techniques between novice and expert workers, and how those techniques could potentially induce possible MSDs at the workplace (Delisle et al., 1996; Plamondon et al., 2010; Gagnon et al., 2016). These studies have looked at some of the variables associated with handling tasks such as foot movements, knee bending, width of the base of support, the lifting dynamics, lifting and tilting strategies, and their potential to reduce the risk of injury during handling operations.

The other side of the biomechanical assessment tool set are kinetic measures, which also provide researchers with valuable information about behavioural changes consistently induced by select controls on occupational demands. Relevant whole-body lifting kinetics include pre-handle anticipatory postural adjustments (APAs) as well as handling behaviors and post-handle corrective responses (Toussaint et al., 1998). A handling motion that involves voluntary multi-joint movements often triggers a displacement in body's centre of mass (CoM), with respect to the base of support, that causes a disequilibrium in the system (Commissaris et al, 1997). In order to counteract such disturbances of balance, individuals initiate APAs, where reactive forces are being created to minimize the CoM perturbations (Bouisset and Zattara, 1981, 1987; Lee et al., 1987). In a bimanual MMH task, the CoM displacement is also affected by the moving of an external load, which causes the combined

CoM (individual and load) to shift with respect to the base of support. Previous studies have indicated that the APAs in bimanual MMH tasks can be observed by analysing the ground reaction force (GRF). For example, the rate of change of the horizontal momentum equals the horizontal component of GRF, and the rate of change of the angular momentum equals the moment effect of GRF with respect to the CoM (Toussaint et al., 1995). Thus, in order to study different handling behaviours associated with bimanual MMH tasks in both typical and controlled conditions, one could carefully analyse the GRF that will make way to comprehend the whole-body kinetics during a handling motion.

When whole-body kinetics are derived for a MMH task, traditional analyses methods tend to focus on specific time points in a handling task, particularly the point at which the highest GRF is being applied to determine instantaneous compressive, shear, and resultant soft tissue loads (Davies et al., 1998). While such methods have useful contributions, they may not provide comprehensive details for a handling motion with respect to continuity and cumulative loading. A system identification paradigm may prove beneficial in these dynamic examples, as system identification provides the capability to represent handling kinetic data in a continuous fashion. Davidson and colleagues (2015) applied a system identification paradigm to a novel seated dynamic stabilization task, and this approach was able to discriminate differences in neuromuscular control of posture between healthy individuals and patients with lower back pain. Davidson et al. (2015) used a 2^{nd} order non-parametric model to simulate the responses they observed during the seating task. By identifying the coefficients in those 2^{nd} order systems, they were able to make inferences on individuals' neuromuscular control over the whole duration of the seating exercise. A similar systems engineering approach may be applied to studying differences in MMH task behaviours, where certain handling patterns could be modeled using mathematical equations. Given the greater degrees of freedom for standing handling compared to seated stationary posture, it is likely a higher order solution might be required. Such a system analysis could prove valuable in categorizing handling behaviours in terms of their risk value, which can then be used in industrial settings to promote safe work environments.

In this study, we conducted a MMH experiment where we attempted to model handling behaviours using conventional methods from motion capture kinematics and postural kinetics, plus by modelling handling behaviors as 5^{th} order non parametric system equations. We attempted to modify handling behaviours by introducing implicit directional visual cues into the MMH task. We hypothesized that different visual cues would induce unique handling strategies among individuals, and hoped our system analysis approach would be able to discriminate handling behaviours by visual cue type.

3.2 Method

3.2.1 Experiment:

Seventy nine healthy university undergraduates (20.74 ± 1.69 years old, 46 female) were recruited and randomly assigned into three visual CUE groups; LEFT ($n = 27$), RIGHT ($n = 27$) and NONE ($n = 27$). Each participant was equipped with 19 reflective markers on their bodies for motion capture with the use of double sided stickers. A horizontally aligned suitcase (72 x 45 x 25cm) was placed on a platform, and vertically adjusted to be at 53% of each subject's standing height (Pentalift, Guelf ON, Canada). Participants were instructed to stand on a force platform (Bertec Corporation, Columbus OH, USA) that was placed directly in front of the height adjusted suitcase (Figure 3.1).

Force platform was calibrated to collect force and moment data in x, y and z directions relative to anteroposterior, mediolateral and longitudinal axes at a sampling rate of 600Hz. A six-camera high speed motion capture system (Vicon Motus, Englewood CO, USA) was calibrated to gather kinematic data of the subjects during their work task at a sampling rate of 120Hz.

3.2.2 Protocol

Each participant was read a script that instructed them on how to handle the suitcase as well as the supposed work environment that we were trying to recreate in the lab. Participants were told that they were suitcase handlers at an international airport, where their job was to pull suitcases on a baggage conveyer from right to left. Given the fact that the hypothetical job environment requires them to repeat this task for 8 hours each day, participants were asked to set their horizontal affordance distance that they perceived to be safe and would keep them injury free during the work day. According to the randomly assigned groups, implicit visual cues were placed on the suitcase to observe if different visual cues would have an impact on the participants' perceived safe affordance and the corresponding suitcase handling techniques. CUE LEFT group was presented with a white color arrow-head glued on top of the suitcase, pointed towards the participants' left side (Figure 3.2). Similarly, the CUE RIGHT group was presented with an exact replica of the arrow-head directed towards participants' right side (Figure 3.2). The CUE NONE group was the control group, without any visual cue provided. Once each participant had selected their safe horizontal affordance distance, suitcase was moved to that exact location and they were asked to move it back (left) towards the initial position to simulate a MMH activity. Each participant repeated the handling motion for three separate trials, and at the end of each trial the suitcase was brought back to the safe horizontal distance picked at the beginning of the experiment. Force platform and the motion capture systems were initiated prior to the movement of the suitcase in order to capture the kinetic and kinematic data of each participant.

Figure 3. 1 The experiment 3 setup. 3.1a (left) shows the posterior-anterior view of a participant standing on a force platform. 3.1b (right) indicates the lateral view of the participant with the suitcase placed horizontally on a sliding rail ready for pulling motion. Participants' were markered up with reflective markers for motion capture.

Figure 3. 2 Horizontally placed suitcase with the two visual cue types. 3.2a (left) shows *CUE LEFT* where the arrow head points towards the left side. 3.2b (right) shows *CUE RIGHT* with the arrow head pointing towards the right side. Three reflective markers were also placed on the suitcase in order to track the suitcase's movement in motion capture.

3.2.3 Analysis

3.3.3.1 Kinetic Analysis

The data collected from the force platform were saved as .csv files. These files contained six columns of data, which accounted for force (F_{x1}, F_{y1}, F_{z1}), and moment (M_{x1}, M_{y1}, M_{z1}) results. The data analysis was performed in Matlab (Appendix C), where they were calibrated and filtered just prior to calculating individuals' antero-posterior center of pressure displacement in x, y and combined directions (CoPx, CoPy, CoPr).

$$CoPx = \frac{M_y}{F_z} \tag{1}$$

$$CoPy = \frac{M_x}{F_z} \tag{2}$$

$$CoPr = \sqrt{CoPx^2 + CoPy^2} \tag{3}$$

In order to accurately analyse the kinetics involved, suitcase handling motion was separated into two stages called *pre-handle* and *post-handle*. These two stages were defined using three onsets, *start-onset*, *grasp-onset*, and *end-onset*. The three onsets were identified using a set of screening algorithms that searched and isolated the specific handling motion events and their corresponding time frames. The *start-onset* represented the beginning of the handling motion, and it was defined as the first instance the participants started rotating their cores (hips and shoulders) to reach for the suitcase. *Grasp-onset* was defined as the first instant participants had their hands placed on the suitcase moments before pulling it towards the end position. It was identified by isolating the time frame where the hands (one or both) started moving horizontally from right to left. Finally, the *end-onset* represented the end of the handling motion, and was calculated by studying the position of one of the reflective markers that was placed on the suitcase. Since the initial resting position of the suitcase was known, the algorithm looked for a set of coordinates that fell within 5 standard deviations of the initial resting position in the y-axis (where the suitcase was horizontally being moved) and recorded its frame number as the *end-onset*. All the data coordinates that fell within the *start-onset* and the *grasp-onset* were categorized as the *pre-handle* stage, whereas the remaining coordinate data starting from the *grasp-onset* till the *end -onset* were categorized as the *post-handle* stage.

The next step of the kinetic analysis was to resample all the *pre-handle* data sets into uniform sized data sets in order to simplify the comparison process. Thus, each *pre-handle* data set was resized into 101 data points using the Fourier transform. Once a set of uniform *pre-handle* kinetic data set was acquired, the final step of the analysis was to characterize the postural behavior of each participant using a nonlinear, non-parametric system identification model. In our system identification paradigm, *U(z)* was the discrete time input signal that represented the normalized affordance distance in the form of a step function. Participants selected these distances as their safest horizontal affordance distance prior to the handling activity. The output, *Y(z)*, was the calculated CoPr displacement values of individuals during the handling period. Once the input and the output signals were defined, we then used Matlab's *system identification* toolbox to model the lifting behaviours in the form of a 5th order transfer function:

$$H(z) = \frac{U(z)}{Y(z)} = \frac{a_0 z^{-1} + a_1 z^{-2} + a_2 z^{-3} + a_3 z^{-4}}{1 + b_0 z^{-1} + b_1 z^{-2} + b_2 z^{-3} + b_3 z^{-4} + b_4 z^{-5}} \tag{4}$$

The system identification toolbox generates mathematical models of dynamic systems with measured input and output data (Mathworks). It accommodates both frequency and time domain data to identify continuous-time and discrete-time transfer functions, process models, and state space models. For the current study, we looked at discrete-time transfer functions that modelled the CoPr displacement in bimanual handling motions. The toolbox allows the user to specify the number of poles and zeroes to be present for each system, and calculates the accuracy of the said transfer function with respect to the measured data set. The poles and zeroes correspond to the coefficients of the transfer function which can provide valuable insight into a system's behavior. In order to successfully model the observed data, we compared a number of different variations of number of poles and zeroes for each trial until a transfer function with the highest accuracy was derived. These transfer functions were then averaged out for each coupling group, and the resulting mean coefficients were compared to analyze the lifting strategies.

3.2.3.2 Kinematic Analysis

Prior to motion capture data collection, a nineteen point joint segment stick figure was created in Vicon Motus software to represent a biomechanically accurate figure of the participants. During testing, reflective markers were placed on these 19 specific joints of the participants so that the infrared cameras could capture the motion of subjects and recreate the biomechanical movements inside a virtual 3D space.

Once the data collection was completed, the software identified the 3D positions of each of the 19 markers and tabulated the coordinate data with respect to time in a .csv file. The next step of the analysis process was to digitize the marker data by connecting the 19 joints to form the full skeleton in each time frame so that we end up with a complete stick figure over the work task time period without any missing data. In the instances where there were some missing marker coordinates, the software used either the cubic reconstruction or virtual reconstruction methods to interpolate missing data to complete each trial. Once the digitization was completed, the data files were saved as Excel files and were used to calculate relative kinematics using the corresponding 3d coordinate data.

For this particular experiment, we were interested in studying individuals' trunk rotation and trunk forward flexion during pre and post suitcase grasping. Thus, the following kinematic formulas were implemented in excel to derive and calculate the two aforementioned metrics.

$$Shoulder\ Twist = tan^{-1}\left(\frac{Shld\_L_y - Shld\_R_y}{Shld\_R_x - Shld\_L_x}\right) \times \frac{180\ degrees}{\pi\ rads} \tag{5}$$

$$Hip\ Twist = tan^{-1}\left(\frac{Hip\_L_y - Hip\_R_y}{Hip\_R_x - Hip\_L_x}\right) \times \frac{180\ degrees}{\pi\ rads} \tag{6}$$

Here, *Shld_L*, and *Shld_R* represent the left and right shoulders respectively, and the subscripts x and y represent the corresponding 3d coordinates that they pertain to. Using the normalized shoulder twist and hip twist values (normalized to the starting shoulder and hip positions), we then calculated the 'x factor' that represented the body twist angle with respect to the initial standing positions:

$$x_{factor} = (|Shoulder\ Twist\ Normalized|) - \ Hip\ Twist\ Normalized \tag{7}$$

Trunk position and forward flexion were then calculated using the following equations:

$$trunk\ displacement = \sqrt{(C7_x - L4L5_x)^2 + \ (C7_y - L4L5_y)^2} \tag{8}$$

$$trunk\ forward\ flexion = tan^{-1}\left(\frac{(trunk\ displacement)^2}{C7_z - L4L5_z}\right) \times \frac{180\ degrees}{\pi\ rads} \tag{9}$$

3.3 Results

3.3.1 Affordances

The safe horizontal affordance distances for all the participants were normalized by their height, and an average horizontal affordance distance value was calculated for each CUE group. The CUE LEFT group had the smallest horizontal affordance (0.131 +/- 0.091 m/m), though this value failed to differ significantly from CUE RIGHT or CUE NONE (0.156 +/- 0.086 m/m and 0.161 +/- 0.079 m/m, respectively). Non-normalised affordances did differ significantly by GENDER ($F(1, 75) = 4.362$, $p=.040$), with males perceiving larger safe affordances. As a CUE x GENDER interaction, males perceived increasingly larger normalized affordances in the CUE RIGHT condition (Figure 3.3), though this interaction failed to reach significance ($F(1, 2) = 2.212$, $p=.117$).

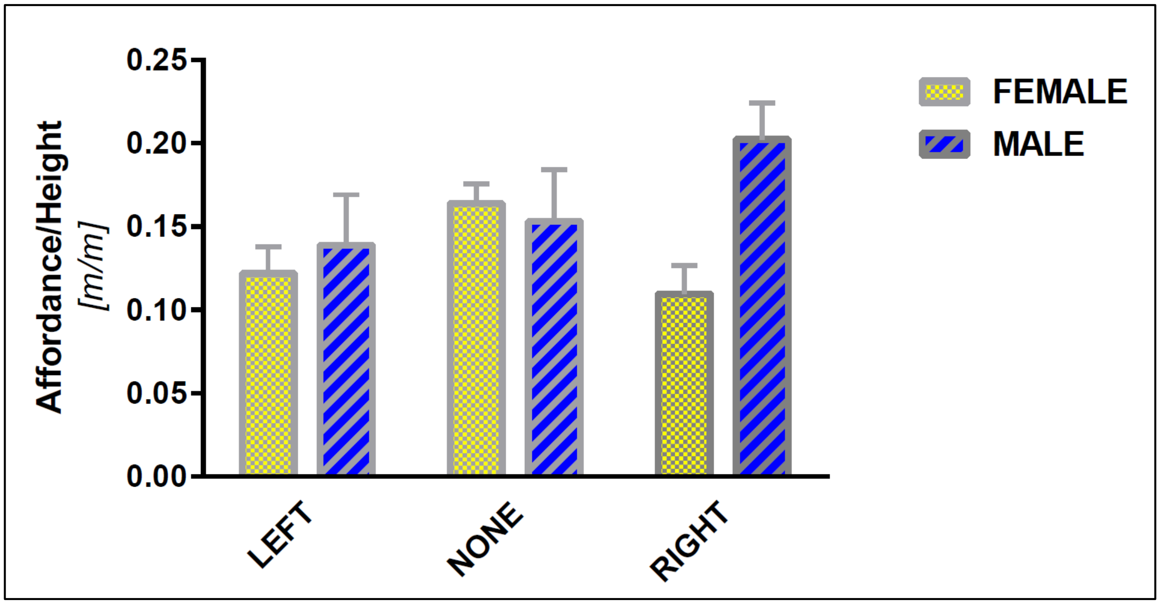

Figure 3. 3 Normalized perceived affordance distances in LEFT, NONE, and RIGHT cued handling conditions. The difference between male and female participants in the CUE RIGHT condition was equal to 15 cm.

3.3.2 Kinematics

The relationship between shoulder and hip angular deflection was defined as X-factor, a commonly used descriptive in sports biomechanics (Kwon et al., 2013) that is also highly relevant in occupational biomechanics. This measure showed a logical relationship to CUE, with small increases from LEFT to NONE to RIGHT conditions as participants increased their twist to initially grasp and handle the load (Figure 3.4). There were no significant CUE or GENDER differences to X-factor.

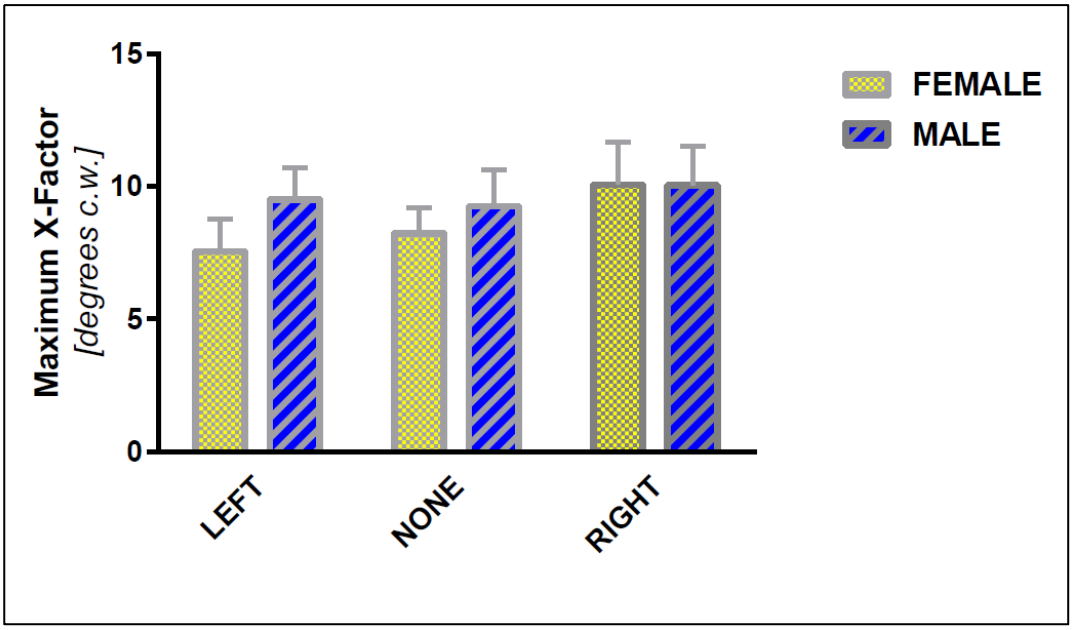

Figure 3. 4 Comparison of the x-factor angle for the three visual cueing groups. X-factor represents the amount of body twist during the suitcase pulling, where large and repetitive twisting of upper torso over an extended period of time has been linked to lower back injury risks (Marras et al, 1994).

These X-factor results are supported by an examination of maximum shoulder rotation values, where males had significantly greater rotations particularly in the CUE RIGHT condition (Figure 3.5), leading to a significant CUE x GENDER interaction ($F(1, 2) = 4.360$, $p=.016$). X-factor magnitudes may have been mitigated by hip rotation, as increased hip rotation decreases X-factor. Maximum hip rotation approached a CUE x GENDER interaction ($F(1,2) = 2.670$, $p=.076$), driven by a significant maximum hip rotation difference in GENDER ($F(1, 75) = 6.749$, $p=.011$), wherein male participants generated greater hip rotation at grasp, particularly in the CUE RIGHT condition (Figure 3.6). The CUE effect on maximum hip rotation was not significant ($F(2, 75) = 2.451$, $p=.093$).

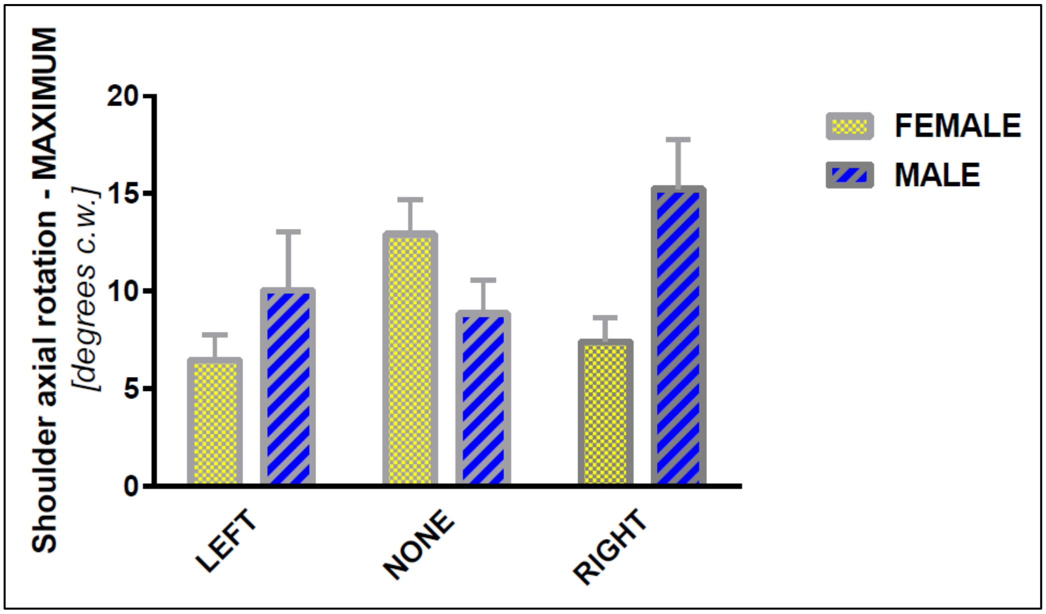

Figure 3. 5 Maximum shoulder rotation angle for the three visual cueing conditions and two gender groups. Male participants had significantly larger rotations in the CUE RIGHT condition.

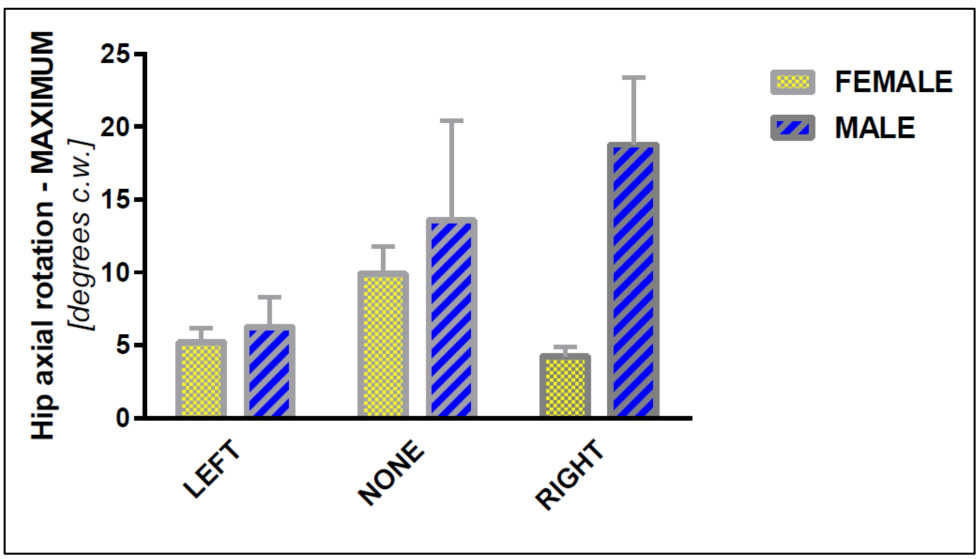

Figure 3. 6 Comparison of maximum hip rotation angle for the three visual cueing conditions and two gender groups. While males had greater real and normalised perceived affordant distances for CUE RIGHT and NONE conditions, they minimised their rotation-driven trunk loading by generating significantly greater hip rotation values (and subsequently smaller X-factor values).

A near significant difference by GENDER also existed for trunk lateral flexion ($F(1, 75) = 3.539$, $p=.064$), with male participants generating greater flexions, particularly in CUE NONE and CUE RIGHT conditions (Figure 3.7).

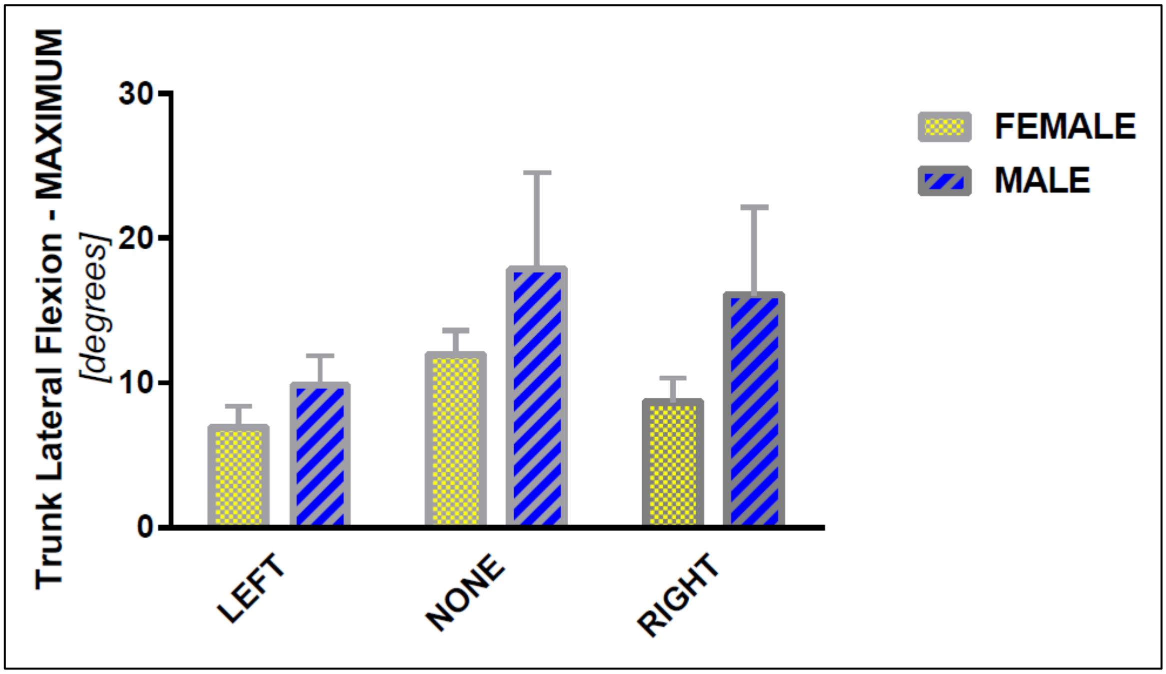

Figure 3. 7 Comparison of maximum trunk lateral flexion angle for the three visual cueing conditions and two gender groups. Males addressed their greater real and normalised perceived affordant distances for CUE RIGHT and NONE conditions by generating greater hip rotation and trunk lateral flexion values.

Axial trunk velocity, another measure commonly associated with occupational overloading (Marras et al., 1994) differed significantly with CUE ($F(2,75) = 4.262$, $p=.018$), with increased velocities in the CUE RIGHT condition for both GENDER groups (Figure 3.8). It is important to note this maximum is for the twist to grasp phase, not the entire movement.

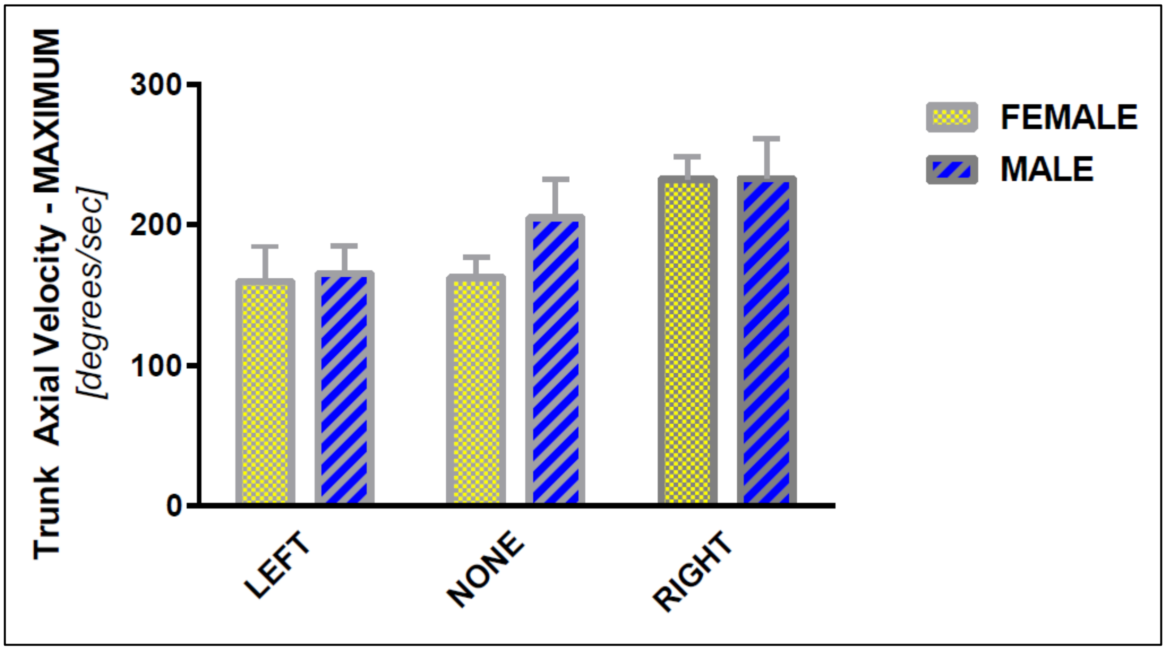

Figure 3. 8 Maximum trunk axial rotation velocity. Both groups used significantly greater velocities to grasp and handle loads in the CUE RIGHT condition.

3.3.3 Kinetics

For each of the three visual cueing groups, an average transfer function was calculated:

$$TF_{control}(z) = \frac{-0.402z^{-1} - 0.404z^{-2} - 0.402z^{-3} + 1.208z^{-4}}{1 - 1.917z^{-1} + 0.993z^{-2} - 0.424z^{-3} + 0.629z^{-4} - 0.279z^{-5}}$$

$$TF_{left}(z) = \frac{-0.137z^{-1} - 0.114z^{-2} - 0.137z^{-3} + 0.388z^{-4}}{1 - 2.731z^{-1} + 2.992z^{-2} - 1.773z^{-3} + 0.509z^{-4} + 0.004z^{-5}}$$

$$TF_{right}(z) = \frac{-0.565z^{-1} - 0.565z^{-2} - 0.565z^{-3} + 1.695z^{-4}}{1 - 2.456z^{-1} + 1.789z^{-2} - 0.164z^{-3} - 0.167z^{-4} + 0.0003z^{-5}}$$

Coefficients (poles and zeroes of the transfer functions) of these 5th order models were compared (Table 3.1). Our results indicate that CUE RIGHT group had the lowest a_0 value and the highest normalized b_0 value (normalized by the corresponding a_0 value) compared to the other two groups. On the other hand, the CUE LEFT group had the highest a_0 value, and the lowest normalized b_0 values among the three groups.

Table 3. 1 Tabulated results of the coefficients a_0 and b_n of the transfer functions for the three visual cueing groups. A_0 value represent the gain of each system that was modelled and is a good indication of the total CoP displacement of the subjects during the work task. B_n values are the damping coefficients and are indicative of the time it takes each participant to regain their balance to come back to the initial CoP position. Results indicate that the CUE RIGHT group had the lowest a_0 value indicating the highest CoP displacement in the negative direction. b_0 value was the highest for the CUE RIGHT group among the three groups, and that corresponds to a faster recovery time in order to counter balance the high CoP displacement.

	$\boldsymbol{a_0}$	$\boldsymbol{b_0 \times a_0}$	$\boldsymbol{b_1 \times a_0}$	$\boldsymbol{b_2 \times a_0}$	$\boldsymbol{b_3 \times a_0}$	$\boldsymbol{b_4 \times a_0}$
CONTROL	-0.40 ± 0.05	0.77 ± 0.30	-0.40 ± 0.20	0.17 ± 0.10	-0.25 ± 0.10	0.11 ± 0.10
LEFT	-0.14 ± 0.05	0.37 ± 0.20	-0.41 ± 0.30	0.24 ± 0.10	-0.07 ± 0.10	-0.0006 ± 0.10
RIGHT	-0.57 ± 0.08	1.39 ± 0.40	-1.01 ± 0.20	0.09 ± 0.10	0.09 ± 0.10	-0.0002 ± 0.10

In systems engineering analysis, transfer functions represent the relationship between a known input and the observed output of a system and thus provide us with some valuable insight into how a system might be processing information and different factors that may affect the outcome of the system. The coefficients of these said transfer functions become increasingly important as each one of the coefficients may correspond to different characteristics of the system. In general, the numerator coefficients (a_0, a_1, a_2, a_3) correspond to the system gain, which determines the size of the steady state response of a system. The denominator coefficients (b_0, b_1, b_2, b_3, b_4) correspond to the damping constants that dictate how much the system oscillates as the response decays toward steady state. These definitions are purely mathematical, however once we apply the system engineering principles into practical applications in order to model various physical systems, parallels can be drawn between the theoretical definitions of the system coefficients and physical characteristics.

Figures 3.9 and 3.10 provide the step response to each transfer function. The results provided us a visual representation of how the visual cueing could affect handling behaviours in terms of individuals' CoPr displacement with respect to time. Results indicated that the CUE RIGHT group had the highest CoPr reach among the three groups, whereas the CUE LEFT coupling group had the lowest CoPr reach.

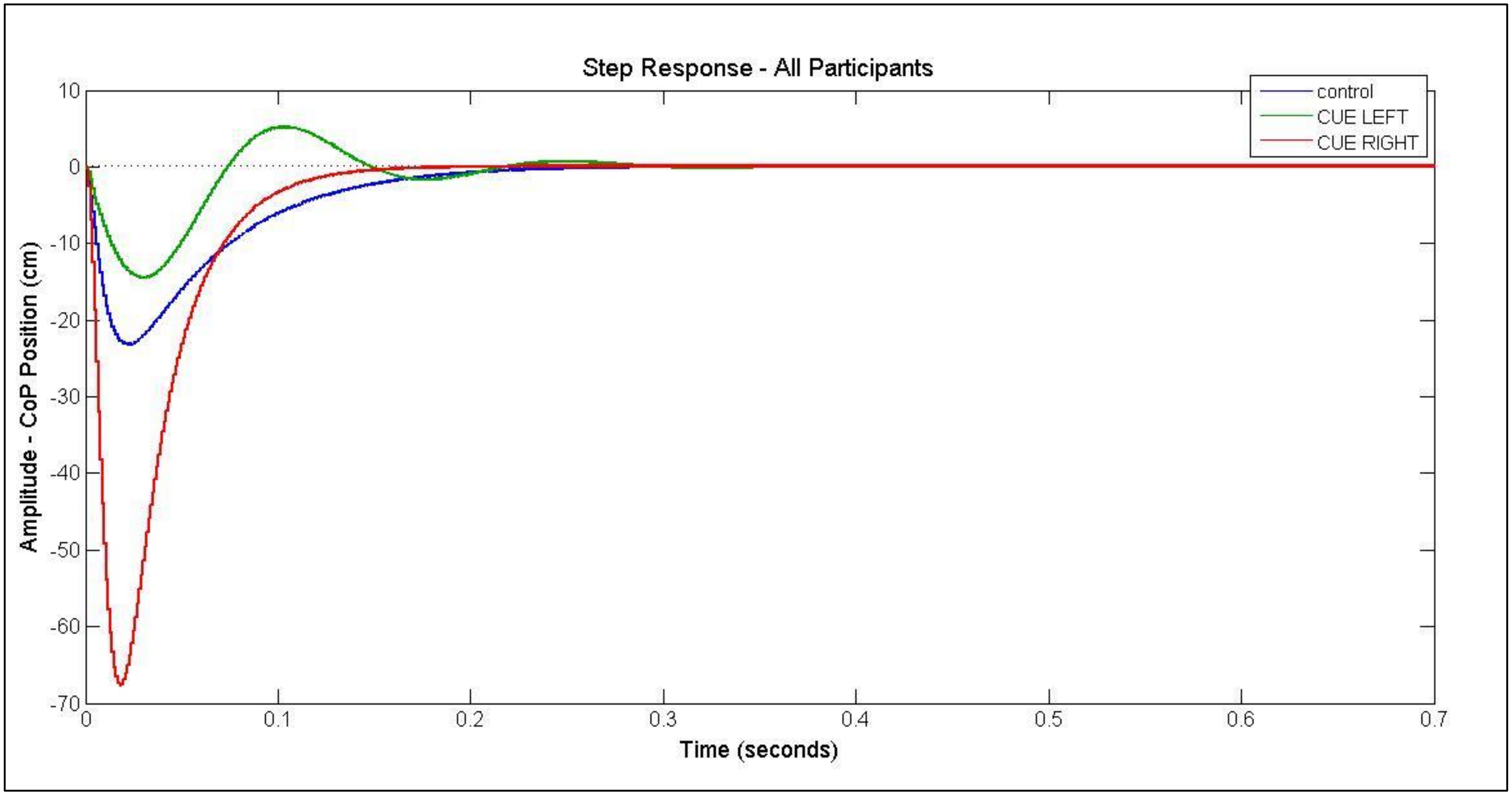

Figure 3. 9 Comparison of the three visual cueing groups' center of pressure (CoPr) displacement during the work task. *Cue-right* group displayed the highest (CoPr) and also the quickest of the three groups to achieve stability as indicated by the time the red line takes to reach the steady state (dotted black line). On the other hand, the *cue-left* group had the shortest CoP displacement, though their time for stabilizing is longer than the *cue-right* group.

Next step of our analysis was to categorize the handling kinetics by gender, and to see whether males and females had reacted differently to visual cueing. The transfer function results were analysed again by sub categorizing into male and females groups within the 3 visual cueing groups. The results displayed a change in behaviour amongst males in our experiment as they had reacted to the visual cues considerably more than the female participants had (Figure 3.10). When compared, the male participants' reaction time towards the CUE RIGHT is considerably longer and vise-versa for the CUE LEFT.

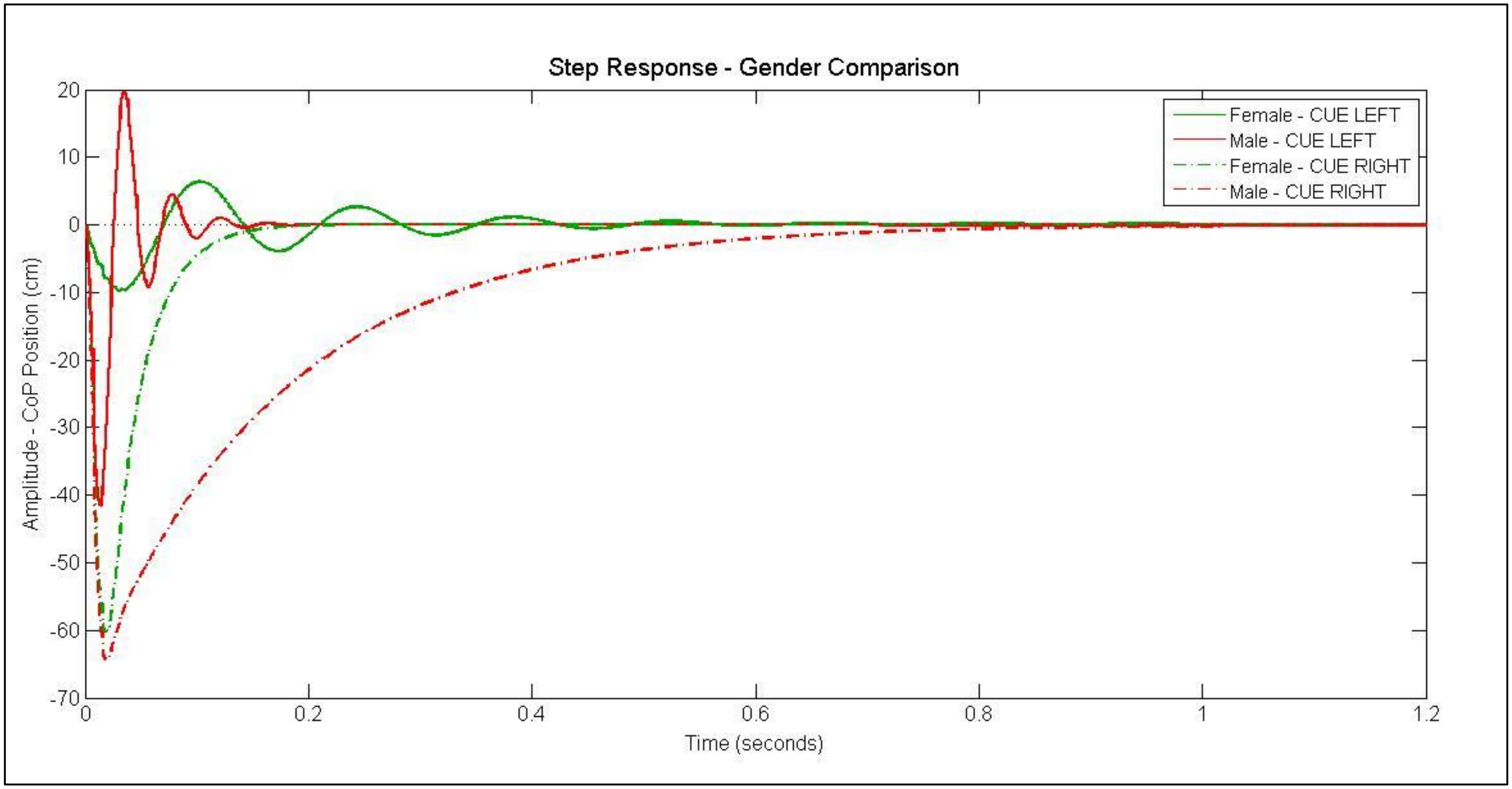

Figure 3. 10 Gender comparison of CoPr displacement results for the suitcase handling task when the visual cues were present. For the CUE LEFT group, male participants displayed an increase in CoPr displacement compared to the female participants, while shortening their settling time (time to initial resting position). As per the CUE RIGHT group, CoPr displacement was increased for both male and female participants. At the same time, male participants' settling time had also increased drastically, indicating a slower return to the starting position when the right cue was present.

3.4 Discussion

The horizontal affordance results indicated a possible link between the cue type and gender, and in combination how those factors could influence what individuals may perceive to be safe during ergonomic tasks. Specifically, the male participants had the highest normalized horizontal affordance with the RIGHT cue, which led us to logically conclude that the visual cue directed away from the participants prompted them to assume a higher reaching distance. These affordance results along with the corresponding handling behaviour results indicated that there were significant differences in kinematics that may have been caused by cue direction. As a result of having higher horizontal affordance on the right side, the male participants would have had to rotate their shoulders and hips at a greater angle (also known as the X-factor) from the starting position. The higher X-factor values would subsequently cause the participants to increase their internal angular velocities while moving the suitcase from right left, which was evident in our axial trunk velocity results that showed increased velocities in the RIGHT cue condition for both gender groups.

Results from the force platform kinetic measures, and the subsequent systems engineering analysis supported the kinematic results, where RIGHT cue had a greater impact on individuals' centre of pressure (CoPr) displacement during the handling task. The step response analysis to the modelled transfer functions displayed the continuous change in CoPr displacement as a function of time. Upon closer inspection, it was observed that the male participants had the highest *settling time*, which is an indication of the amount of time taken to reach CoPr equilibrium, when the handling task is completed. This is a direct consequence of having a greater horizontal affordance distance at the beginning of the work task, where the male participants would have to take longer than average amount of time to rotate their bodies back to the initial standing position.

The unique nature of our results favoring gender based correlations that prompted male participants' MMH behaviours to be influenced by visual cueing could be explained by previous research conducted on the subject of gender based perceptual differences. Previous researchers have shown that males have greater bilateral brain activity during visuospatial tasks whereas females have greater bilateral brain activity during phonological tasks (Dittmar et al., 1993; Clements et al., 2006). Our suitcase handling experiment coupled with visual cueing is very much a visuospatial task, thus it may have prompted greater attention from male participants, which corresponds to triggering greater interest in a target, in our case, the visual cues (Jacob & Karn, 2003).

The use of motion capture and force platform systems to study ergonomic behaviours, particularly kinematic and kinetic measures, provide researchers with multiple options to identify detailed biomechanics and work techniques associated with MMH tasks. Combined with custom experimental software capable of assessing kinematics and kinetics simultaneously, these bio-instrumentation systems could prove valuable in categorizing handling behaviours in terms of their risk value, which might then be used in industrial settings to promote safe work environments.

4.0 Global Discussion

4.1 Introduction

Bio-instrumentation allows the study of biological systems, through the use of bio-electronic instruments that integrate sensors, interface electronics, microcontrollers, and computer programming to capture micro and macro behaviours, and thus offer relevant information and solutions in the fields of medicine, biomechanics, and ergonomics. Occupational biomechanics, the study of the physical interaction of workers with their tools, machines, and materials so as to enhance the workers' performance while minimizing the risk of MSDs is a challenging research area, due to the multiple interactive factors that are associated with work context and worker perceptions and behaviours. The use of bio-instruments allows occupational biomechanics investigators to analyze the physical and psychosocial factors by combining experimental paradigms and measures from multiple disciplines such as biology, optics, mechanics, physics, electronics, and computer science. Occupational bio-measurements such as visual attention, 3D kinematics, and ground reaction forces can be measured using standalone bio-instruments. However, combining multiple bio-instruments in experimental settings has the potential to yield more explanatory ergonomic analyses. For example, understanding the postural adjustments a fatigued worker makes to control an unstable load might measure visual and haptic perceptions, whole body kinetics and kinematics, plus relevant muscle activities. Furthermore, continuing advancement in bio-technology allows researchers to constantly update existing bio-instruments, introducing new instrumentation techniques to expand our understanding of work, efficiency, and behaviour.

Standalone bio-instruments that are commercially available today have two main components: hardware and analysis software. Hardware are the physical components of bio-instruments, whereas the analysis software allows the researchers to perform various data analytics on the corresponding bio-data. A majority of the bio-instruments in the industry today come equipped with built-in software that permit a set number of analysis methods that are highly efficient, but limiting the users into fixed forms of analyses, and subsequently limiting them from further expanding their research. Custom built experimental softwares, on the other hand, allow the researchers to program their own analysis methods enabling well-structured high-level analyses that may allow deeper discussions with regards to data analysis. Furthermore, custom experimental software has the ability to synchronously incorporate multiple bio-instruments into one experimental setup and to perform comprehensive data analyses between and within the instruments that are involved in the setup. Previous researchers have often focused on select perspectives of worker behavioural analyses, by performing single instrument experiments with corresponding local data analyses (Cappelli & Duffy, 2006). In order to understand the perceptions and actions at work, however, psychophysics methodologies coupled with multiple bio-instrument setups may be required, which in turn may unravel the "bigger picture", helping us to understand how perceptions and actions are coupled in occupational activities.

The current thesis attempts to start the design and face validation of a 21st century occupational psychophysics toolbox, by combining typically standalone bio-instruments and custom experimental software capable to analyze bio-instrumentation data. In particular, my goal was to examine psychological and physical interactions that are relevant in industrial tasks when assessing risks of work related MSDs. The hardware suite of the bio-instrumentation setup featured a mobile vision tracking system, a passive marker motion capture system, and a pair of force platforms with the goal of providing a comprehensive biomechanical assessment within a simulated occupational workstation. The custom Matlab softwares complemented the hardware by introducing algorithms capable of functions including image and attention processing, full body linear and angular kinematic measurement, and ground reaction force analyses that could assist biomechanists and ergonomic researchers to study unique and integrated characteristics of perception-action coupling in occupational behaviors. I conducted two unique MMH experiments that were designed to test participants' visual attention, preparatory and action handling kinematics, and kinetic profiles in a simulated work place, which could collectively shed light on perception based ergonomic actions and work-related musculoskeletal disorders.

4.2 Study 1

In chapter 2, I designed a pair of experiments that generated specific motivational states amongst participant 'workers' performing a MMH task, to observe how positive or negative motivational states could drive corresponding behaviours, specifically MMH perceptions and actions. I simulated a baggage (suitcase) handling environment, where 'workers' would experience specific motivational states thanks to a fixed script with combined mental, physical, and environmental factors, delivered by the investigator. By measuring each individual's motivation to perform a handling task on a Likert scale of 'very bad' to 'very good' prior to the completion of the work task, and analysing the participants' handling techniques, I hoped to differentiate how positive and negative motivational states could influence MMH perceptions and actions that might eventually lead to work related musculoskeletal injuries.

Visual attention is one of the key perceptual contributors in the process of selecting and guiding human actions, and provides great insight into the relationship between psychophysical states of individuals and their subsequent actions (Vickers, 1992). Previous research supports the idea that visual attention precedes human behaviours (deBruin et al., 2014), thus providing experimenters an opportunity to empirically connect perception and action in MMH, and to test ergonomic strategies that might shape behaviours. Given that, I used mobile vision tracking goggles within the MMH task to allow the participants' visual attention prior to the work task, to be carefully observed.

My results from Study 1 in chapter 2 indicated a clear connection between participants' motivations and their corresponding handling actions. There was a significant difference between frequency of unimanual and bimanual grasp selected based on state condition, wherein the odds ratio showed that the odds of selecting a unimanual grasp were 6.05 times higher with the positive motivation state than the negative motivation state. Vision tracking results supported these findings, identifying a greater number of fixations and relatively longer fixation durations directed at the centre of the suitcase for the positive motivation state group compared to the negative motivation state group.

These results seem to follow the theory of 'self-efficacy' introduced by Albert Bandura that refers to an individual's belief about his or her capabilities to execute a specific task within a given context (Bandura, 1977; Stajkovic & Luthans, 2003). There are a number of determinants of self-efficacy, but relevant factors for worker behaviours is primarily physiological and psychological arousal, which logically combine to influence motivation and action in worker behaviours. Self-efficacy is measured on two scales: Magnitude, the level of task difficulty that a person believes he or she is capable of executing; and strength, which indicates whether the individual's belief about magnitude is strong and likely to produce perseverance in coping efforts, or weak and easily surrender in the face of difficulty. In my case, the results could be interpreted as positive motivation group possessing high levels of self-efficacy by predicting low magnitude and subsequently high strength to handle the suitcase, thus prompting unimanual handling. On the other hand, the negative motivation group may have had low self-efficacy due to their high estimation of task magnitude and a relatively lower perceived strength to complete the task, resulting in bimanual handling techniques.

4.3 Study 2

Better understanding of human perceptions and behaviours at the workplace may be an important first step in minimizing workplace injury occurrences. However, it is also important to identify the ways to correct and modify human behaviors at workplace using practical methods. In the second experiment from Chapter 2, I studied the use of implicit visual cues for modifying MMH behaviors. Previous research has shown that visual cues do accommodate in changing actions, typically reaction times, by automatically triggering orienting of attention (Posner, 1980; Tipples, 2002). Although the influence of explicit and implicit cues on visual attention is well known, their effectiveness in moderating occupational handling tasks and work-related activities requires further research. By employing vision tracking, we expected to confirm previous findings of visual cues influencing visual attention, while studying how cues could potentially affect perceptions and actions during MMH tasks. The visual cues were arranged in two different orientations such that they provided either a conventional cue or a counter cue to the handling behaviours observed in Study 1. Orientation 1 - Two triangles pointing to either side of the suitcase positioned close to the centre of the suitcase (counter cue – positive script; conventional cue – negative script). Orientation 2 - A single triangle pointing to the front handle positioned near the centre of the suitcase (counter cue – negative; conventional cue - positive). The placement of the visual cues was strategically designed to influence participants' preferred handling methods, and we hoped to find potential changes in handling techniques as well as pre-action visual attention when the cues were presented. By exposing individuals to varying motivational states and implicit visual cues, and measuring their visual attention, we wanted to perform a thorough analysis of perceptions and actions at work, while exploring potential methods of modifying such behaviours in a simulated workplace environment.

Results from Study 2 confirmed my findings in experiment 1 with regards to positive and negative states having an influence over participants' handling techniques. The new information also confirmed that visual cues had influenced handling techniques. Conventional cues reinforced the handling behaviour from experiment 1, particularly in combination with the negative motivation state, where 100% of participants preferred bimanual handling. Counter cues on the other hand yielded a mixture of unimanual and bimanual grasps under the negative motivation state. For the positive motivation state, the association between the type of cue and whether a unimanual or bimanual grasp was selected was not significant, suggesting that a unimanual grasp was typically selected with the positive script regardless of the type of cue. Vision tracking results also supported these findings, where the positive motivation group continued to direct a concentrated fixation on the front handle despite the counter cues, indicating the preferred unimanual handling technique. In contrast, the negative motivation group directed attention at the counter cue, despite still choosing a bimanual handling action 61.1% of the time. These results support the potential of a single implicit cue to attract attention, though that attention failed to influence participants' handling actions significantly.

4.4 Study 3

In chapter 3, we implemented a similar experimental paradigm with a different set of bio-instruments to study individuals' kinematic and kinetic profiles during a MMH task. In the past, researchers have often experimented with various instruments in order to collect kinematic data from workers. Marras and colleagues developed a lumbar motion monitor exoskeleton to capture three dimensional kinematics, specifically the instantaneous change in trunk position, velocity and acceleration, in order to assess the risks of back injuries (Marras et al., 1992). The use of motion capture systems along with force platforms to measure full body kinematics and ground reaction force kinetics is a common practice in today's biomechanics research (Kim et al., 2013). A more recent study performed an analysis of occupational hygiene among airport baggage handlers by focusing on workers' trunk and upper arm angular changes, velocities, and accelerations, and aimed to differentiate the correlations between postural exposures in different workstations (Wahlstrom et al., 2016). We simulated a similar suitcase handling task coupled with implicit visual cueing, in order to examine how visual cues may influence individuals' perceived safe horizontal affordances. The two bio-instruments were then used to observe and analyze how the corresponding horizontal affordant distances may dictate participants' MMH behaviours, in particular their handling biomechanics.

Our results indicated that there were significant differences in kinematics that may have been caused by cue direction. The relationship between shoulder and hip angular deflection, also known as the X-factor, showed a predicted relationship to cue type, with small increases from LEFT to NONE to RIGHT cue conditions as participants increased their twist to initially grasp and handle the load. In particular, male participants had significantly greater shoulder and hip rotations in the RIGHT cue condition. Axial trunk velocity, another measure commonly associated with occupational overloading (Marras et al., 1994) differed significantly with cue type, with increased velocities in the RIGHT cue condition for both gender groups. Results from the kinetic analysis and the subsequent systems engineering analysis supported the kinematic results, where RIGHT cue prompted greater centre of pressure (CoPr) displacement among the participants during the handling task. The step response analysis to the modelled transfer functions displayed the continuous change in CoPr displacement as a function of time, and highlighted that male participants had a greater settling time for RIGHT cue condition as a result of greater horizontal affordant distance.

The unique nature of our results favoring gender based differences that prompted male participants' MMH behaviours to be influenced by visual cueing could be explained by previous research conducted on the subject of gender based perceptual differences. Previous researchers have shown that males have greater bilateral brain activity during visuospatial tasks whereas females have greater bilateral brain activity during phonological tasks (Dittmar et al., 1993; Clements et al., 2006). Our suitcase handling experiment coupled with visual cueing is very much a visuospatial task, thus it may have prompted greater attention from male participants, which corresponds to triggering greater interest in a target, in our case, the visual cues (Jacob & Karn, 2003).

4.5 Software Development

As much as the hardware components of the bio-instruments are useful in collecting data and designing experiments, the software system that complement the instruments while allowing high level analyses play an equally important role in our attempt in designing the psychophysics toolbox. Using Matlab, a multi paradigm numerical computing environment and a fourth generation programming language, we had the capability to create algorithms to address any analytical need starting from simple tasks such as data filtering and data manipulation, to more complex analytical tasks including mathematical modelling and bio-instrument specific variable derivation.

4.5.1 Vision Tracking Software

For vision tracking, different algorithms were created in order to process raw eye tracking coordinate data, and to compare visual attention of individuals by quantifying the results. I used an already existing Matlab based eye-tracking software named 'EyeMMV' (Krassanakis et al., 2013), and made necessary coding modifications to its subroutines in order to perform the customized vision tracking analyses I was interested in. 'Heat-maps' in particular was one of the functions that was looked at as a method of visually representing eye-tracking results. Heat maps are used to emphasize the strength of fixations by combining the number of fixations and the durations of those fixations (Spakov et al., 2007). The algorithm make use of different color schemes that generally demonstrate the areas on a screen where the subject's visual attention was heightened with respect to other areas. I also developed a novel vision tracking functionality called the Attraction Index

(AI). The AI is a number, calculated in order to compare the visual attention of two or more fixation points. For the purpose of current study, the (AI) identified and quantified the strength of eye-fixations by taking three main factors into account; number of fixations (number), duration of each fixation (duration), and the relative distance (distance) of each fixation from one of the three handles of the suitcase. AI may provide an excellent indicator of the pre-movement visual attention.

4.5.2 Kinetic Analysis Software

Traditional kinetic algorithms were programmed and applied to the force platform data to analyze full body and segmental biomechanics. Three dimensional force and moment data collected from the force platforms were used to calculate the antero-posterior center of pressure displacements in x, y and combined directions (CoPx, CoPy, CoPr). These measures are often used to derive and isolate external forces acting on different body segments. At the same time, I explored a novel kinetic analysis method through Matlab algorithm development, where the goal was to model MMH biomechanical movements into mathematical models using a systems engineering approach. In the system identification paradigm, the input signal was the normalized affordance distance in the form of a step function. Participants selected these distances as their safest horizontal affordance distance prior to the handling task. The output was the calculated CoPr displacement values of individuals during the handling period. Once the input and the output signals were defined, we then used Matlab's *system identification* toolbox to model the lifting behaviours in the form of a 5^{th} order transfer function. By doing so, I expected to isolate some of the finer kinetic details that may become visible, and help us in understanding the biomechanics of handling tasks comprehensively.

4.5.3 Synthesis

Numerical analysis software such as Matlab, allows the researchers to make use of numerous built-in functionalities along with programing capabilities to develop novel analytical models from ground up that could ultimately result in comprehensive data analyses. Furthermore, matlab's graphical user interface functionalities make it relatively easier to append multiple algorithms into one program, allowing the luxury to continuously upgrade the analysis software by bringing in new instruments. Therefore, the back-end code along with the graphical user interface act as the 'toolbox' that complements the hardware by creating a virtual space for multiple standalone bio-instruments to exist as part of a larger system.

The current thesis' attempt to expand the perception-action paradigm in occupational tasks for the purpose of injury prevention and modifying worker behaviors is a timely subject. As the bio-instrumentation technology is constantly on the rise, the need to use such instruments collectively at the work place in order to understand perceptions and actions during everyday tasks is quite relevant. Employers are constantly exploring ways to strengthen their workforce by preventing injuries and promoting safe work procedures. Thus, seeking help from the biomechanists and ergonomists who conduct research on the physical and perceptual behavioural implications at workplaces may be the best possible method of addressing such issues. The current thesis used three different bio-instruments that are commonly found in biomechanical laboratories, and combined them with custom Matlab software for analysis in a simulated experimental space where we were in charge of controlling the independent variables that needed attention. In the real world however, the closely linked perception-action relationship is a difficult challenge to tackle in such a short term with limited resources, though the work completed in this thesis does provide certain solutions that may prove useful to the ergonomic community going forward.

4.6 Limitations

One of the main challenges ergonomists have is the subjective nature of assessing occupational tasks. As a result, at times it has proven unsuccessful trying to quantify physical and mental stressors that are associated with such tasks. Therefore, a set of bio-instruments capable of representing an “acceptable limit” in ergonomic activities would prove valuable to researchers trying to understand the worker perception of tasks involving occupational stressors. As a combined unit, the hardware and software from my ‘psychophysics toolbox’ offer such capabilities with motion capture and force platforms providing the biomechanical and physiological measurements that define acceptable limits for work stressors, while vision tracking provides insight into individuals’ pre-action strategies and their visuospatial awareness. The software component compliments the hardware by signal processing, data analysing, and visually representing results to the readers.

Our experimental work provide evidence supporting the perception-action theory where certain actions could be influenced by changing preceding perceptions. It was also observed that ergonomic actions could be moderated with the help of implicit visual cueing as found by previous researchers (Posner, 1980). However, a number of challenges do arise when we attempt to transfer our experimental work into real world applications. First and foremost, it is a quite difficult task to simulate an exact replica of workplace like environment in a biomechanical lab. A typical work shift of a MMH worker runs for eight hours with a total of one hour break time in between. This would imply that the worker may have to perform their handling tasks non-stop for couple of hours at times. However, when we try to simulate a work task in the lab, the task is typically repeated only for 3 to 5 trials with considerable rest time in between. Thus, it does not replicate the same fast pace work environment with added physical and mental stressors that could potentially induce different workable actions from individuals in a lab compared to the actual workplace. Secondly, the bio-instrumentation setups used for biomechanical testing are not mobile in most cases, and requires considerable amount of time and manpower to set up and calibrate, which could potentially prevent employers from seeking help from the ergonomic researchers. There is also a case to be made on how feasible it is to have bio-instrumentation setups at workplaces measuring individuals' actions while not disturbing the normal workplace environmental equilibrium. Therefore, transferring experimental work from a laboratory to an actual workplace needs to be carefully monitored and may only be done with appropriate collaboration of employers and ergonomic researchers.

4.7 Future Directions

Going forward, our work in bio-instrumentation and studying human perception and actions for work related tasks could play a huge role in identifying unsafe work practices and minimizing potential ergonomic injuries. As the bio-technology industry make further developments, more and more novel bio-instruments and systems are being introduced to the scientific community. As mentioned earlier, the main challenge the researchers face today is to figure out how to transfer the experimental setups from the laboratory to an actual workplace, and that is where newer technologies may provide more appealing opportunities to the employers to implement such human measurement units at workstations. Marker-less motion capture systems per instance may prove to be a more cost and time effective method to implement at workplaces, where the workers would be free to continue their normal work routines without much disturbance from the testing equipment. Virtual reality devices in the form of safety goggles and head shields are being implemented in workplaces to modify worker visual attention patterns thus promoting safe visuospatial awareness among workers. In the current thesis, we only used 3 bio-instruments, but going forward we could include more relevant bio-instruments to make the whole system work more efficiently. Heart rate monitors and inertial measurement units are two such instruments that would provide the researchers a lot more information regarding the workers perceptual and action related behaviours.

Overall, the work that has been done in this thesis is may be important to the ergonomic community, and has multiple applications to other related industries. Further research and resources are required to expand and fine-tune the psychophysics toolbox in order to transfer its effectiveness to the real world applications.

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Appendix A

Scenario 2: Baggage transferring environment (Script)

You are a baggage handler at an international airport, a position you've held for the past 24 months without promotion or increased wage. Your job is transferring suitcases horizontally from the baggage train in front of you to a baggage conveyor on your left. This task is performed 5 times per minute for an 8 hour shift, which would include 7 hours of work and 1chour of breaks. Your specific assigned flights are weekend charters to sunny San Diego, so your average suitcase handled has a mass equal to the items an adult would bring on a weekend away at a resort.

When I say 'LOOK', your target suitcase will be revealed. We want you to look at the suitcase and find where you are going to grasp it to handle it for the next suitcase transfer of your work shift. Only look, do not reach, until you hear the second command, which will be 'REACH'. When you hear reach, we want you to reach out and grasp the suitcase so you are ready to handle it for the next suitcase transfer of your work shift. Do not move the suitcase, merely grasp and hold until you hear the word 'STOP'.

READY?

<Start eye tracker now>

<3 seconds>

LOOK

<10 seconds>

REACH

<10 seconds>

STOP.

Appendix B

Vision Tracking Analysis Code

```
%This function converts eye tracking data (excel/csv) files into txt files
%so that they can be used with the software 'eyeMMV'. It also filters out
%the noise (caused by blinking) so that the resulting text file can be used
%straightaway to analyze using 'eyeMMV'

function text_converter (data)

%save the input file name
[~,name,~] = fileparts(data);
fname = [name,'.txt'];

%read in the excel file
[rawData]  = xlsread(data);

%eyeMMV only requires three parameters; x-cordinate, y-cordinate and the time
%(frame number in our case) to analyse eye tracking data. So we make three
%separate column vectors from the input excel file
xcord = rawData(:,7);
ycord = rawData(:,8);
time  = rawData(:,1);

%correction for data files containing abnormal coordinate values.
%for k = 1:length(ycord)
%    ycord(k)= ycord(k)+1999;
%end

%correct all the abnormal cordinate values to -2000. i.e: cordinates should
%be between 768x576

[m,~]=size(rawData);

for i = 1:1:m
   if xcord(i,1) >768
       xcord(i,1) = -2000;
   elseif ycord(i,1)> 576
       ycord(i,1) = -2000;
   end
end
%combine the three column vectors to make a matrix
c = [xcord ycord time];

%now to remove the blinking noise. Our eyetracker displays bliniking noise
%as (-2000). So we remove any x or y cordinate value that is less than
%zero.

%step one: create an identical matrix but with the absolute values in it
a = abs(c);
```

```
%step two: compare the two matrices and then if the values are different, we
%assign a zero to that particular location of the value
[~,loc]= ismember(a,c,'rows');
%step three: get rid of all the locations (rows) containing the zeroes
%(that corresponds to -2000 value)
b = c(nonzeros(loc),:);

%take the transpose matrix, required for fprintf function
d = b';

%write the resulting matrix to a text file
%dlmwrite('.txt',b,'delimiter','\t','precision',4);

fileID =  fopen (fname,'w');
fprintf(fileID,'%6.2f %8.2f %6.0f\r\n',d);
fclose(fileID);

end
```

……

```
%Combine_fixations function
%file works with 'fixation_plots.m' file where it calculates the attraction
%index of different handling techniques.
function combine_fixations(fix_list,ref_list,t1,m1,m2,m3)

m = 1;
[x1,y1,x2,y2,x3,y3,a1,a2,a3,delta_a1,delta_a2,delta_a3] =
fixation_plots(fix_list,ref_list,t1,m,m1);
% fprintf ('The Weighted Attraction of Positive Centre is %d \n', a1);
% fprintf ('The Weighted Attraction of Positive Right is %d \n', a2);
% fprintf ('The Weighted Attraction of Positive Left is %d \n', a3);
positive = [a3 a1 a2];
delta_positive = [delta_a3 delta_a1 delta_a2];

figure
plot(x1,y1,'bo')
hold on
plot(x2,y2,'bd');
hold on
plot(x3,y3,'bs');
hold on

[x1,y1,x2,y2,x3,y3,a1,a2,a3] = fixation_plots(fix_list,ref_list,t1,m1+1,m2);
% fprintf ('The Weighted Attraction of Negative Centre is %d \n', a1);
% fprintf ('The Weighted Attraction of Negative Right is %d \n', a2);
% fprintf ('The Weighted Attraction of Negative Left is %d \n', a3);
negative = [a3 a1 a2];
delta_negative = [delta_a3 delta_a1 delta_a2];

plot(x1,y1,'ro')
```

```
hold on
plot(x2,y2,'rd');
hold on
plot(x3,y3,'rs');
hold on

[x1,y1,x2,y2,x3,y3,a1,a2,a3] = fixation_plots(fix_list,ref_list,t1,m2+1,m3);
% fprintf ('The Weighted Attraction of Neutral Centre is %d \n', a1);
% fprintf ('The Weighted Attraction of Neutral Right is %d \n', a2);
% fprintf ('The Weighted Attraction of Neutral Left is %d \n', a3);
neutral = [a3 a1 a2];
delta_neutral = [delta_a3 delta_a1 delta_a2];

plot(x1,y1,'go')
hold on
plot(x2,y2,'gd');
hold on
plot(x3,y3,'gs');
hold on

plot([-160 160],[0 0],'k','LineWidth',1.5);
hold on
plot ([0 0],[-40 40],'k','LineWidth',1.5);
hold on
plot ([-110 -110],[-40 40],'k','LineWidth',1.5);
hold on
plot ([110 110], [-40 40],'k','LineWidth',1.5);

% text(0,0,'\leftarrow Front Handle');

title (sprintf('Fixations with respect to the three Handle Locations (Filter Radius = %d
pixels)',t1),'FontSize',20);
xlabel(sprintf('Normalized Horizontal Pixel Coordinate \n (Percentage
Values)'),'Color','k','FontSize',15);
ylabel(sprintf('Normalized Vertical Pixel Coordinate \n (Percentage
Values)'),'Color','k','FontSize',15);
xlim([-160 160]);
ylim([-40 40]);
%axis equal;
set (gca,'XGrid','on','YGrid','on');
set (gca,'Xtick',-160:10:160);

set (gca,'XtickLabel',-50:10:50);
legend ('Positive - Centre','Positive - Right','Positive - Left','Negative - Centre','Negative -
Right','Negative - Left','Neutral - Centre','Neutral - Right','Neutral - Left');
% v = get(h,'title');
% set(v,'string','Fixations');

disp([positive; negative; neutral]);
y = [positive;negative;neutral];
delta_y_upper = [delta_positive;delta_negative;delta_neutral];
```

```
errorbar_lower=zeros(size(y));

% set (gca,'YGrid','on');

%errorbar_groups(y,errorbar_lower,delta_y_upper);
figure
bar (y)
set (gca, 'YGrid','on');
%set (gcf,'XTck',1:3);
set (gca,'XTickLabel',{'Positive','Negative','Neutral'});
legend ('Left Handle','Front Handle','Right Handle');
% title ('Attraction Index of the Suitcase Handles','FontSize',20);
xlabel ('Motivation','FontSize',15);
ylabel ('Attraction Index','FontSize',15);

end
```

………

```
%Function fixation_plots compares a set of fixation points with a set of
%reference points and plot them on a normalized cartesian plane
function
[x_cen_diff,y_cen_diff,x_right_diff,y_right_diff,x_left_diff,y_left_diff,a1,a2,a3,delta_a1,delta_a2
,delta_a3]=fixation_plots(fixation_list,coordinate_list,t1,n1,n2)

%input files, reference coordinate list and the fixation coordinate list
data = load(fixation_list);
ref_points = load(coordinate_list);

%separate fixation points into x and y coordinates
x_data = data(:,1);
y_data = data(:,2);
duration = data(:,7);

%separate reference points into x y coordinates and also group into three
%sections; centre, right and left (corresponds to the three handling points)
x_centre = ref_points(:,1);
y_centre = ref_points(:,2);
x_right = ref_points(:,3);
y_right = ref_points(:,4);
x_left = ref_points(:,5);
y_left = ref_points(:,6);

%initialize matrices and arrays to be used in calculating the difference
%between the reference points and the fixation points
table5 = zeros(5);
table2 = zeros(5);
table1 = zeros(5);
x_left_diff = [];
y_left_diff = [];
x_right_diff = [];
y_right_diff = [];
```

```
x_cen_diff = [];
y_cen_diff = [];

r_cen_diff = 0;
r_right_diff = 0;
r_left_diff = 0;

a3 = [];
r_left_inv = [];
dur_left = [];
dur_right = [];
dur_cen = [];

%n1 and n2 represents the first and the last data set to be considered from
%the complete fixation and reference point list. Note that all three
%scenarios' data have been input as a single file but are in the order of
%positive, negative and neutral. So we first assess the positive set of
%data, so n1 and n2 tells the program up until which data point each
%scenario runs
for i = n1:n2
   %calculate distance between the reference point and the fixation point
   %using the function distance2p for centre, right and left coordinates
   d1 = distance2p (x_data(i),y_data(i),x_centre(i),y_centre(i));
   d2 = distance2p (x_data(i),y_data(i),x_right(i),y_right(i));
   d3 = distance2p (x_data(i),y_data(i),x_left(i),y_left(i));

   %check whether the distances calculated above are within the user
   %required range. t1 is the radius distance to be defined by the user to
   %filter out any non-required fixation points
   if d1<t1
      table1(i,:,:,:,:) = [x_data(i),y_data(i),x_centre(i),y_centre(i),duration(i)];
   else if d2<t1
         table2(i,:,:,:,:) = [x_data(i),y_data(i),x_right(i),y_right(i),duration(i)];
      else if d3<t1
            table5(i,:,:,:,:) = [x_data(i),y_data(i),x_left(i),y_left(i),duration(i)];
         end
      end
   end
end

%remove all rows containg all zeros. 'any' function checks whether the
%table 1 has zeros in each row (2 represents search by row) and produces a
%column vector containing 1's and 0's for corresponding values (0 for zeros
%and 1's for other values). ~ means logical NOT
table1(~any(table1,2),:) = [];
table2(~any(table2,2),:) = [];
table5(~any(table5,2),:) = [];

%length of each data set; table 1 --> central coordinates; table 2 -->
%right coordinates, table 3 -->left coordinates
p = length(table1(:,1));
```

```
q = length(table2(:,1));
r = length(table5(:,1));

% disp(table2);
%fprintf ('number of left neutral fixations is %d\n',r);

for i=1:p
    x_cen_diff(i)= (table1(i,3) - table1(i,1))/768*100;
    y_cen_diff(i)= (table1(i,4) - table1(i,2))/768*100;
    r_cen_diff(i)= sqrt(x_cen_diff(i).^2 + y_cen_diff(i).^2);
    %r_cen_inv(i) = 1/r_cen_diff(i);
    dur_cen(i) = table1(i,5);
end
% x_cen_diff = x_cen_diff/768 * 100;
% y_cen_diff = y_cen_diff/576 * 100;


% disp([x_cen_diff' y_cen_diff' r_cen_diff']);
%a1 = mean(r_cen_inv);
a1 = p * mean(dur_cen)/sum(r_cen_diff);
delta_a1 = sqrt((mean(dur_cen)^2 + p^2 +
(mean(dur_cen)^2+p^2)/sum(r_cen_diff)^2)/sum(r_cen_diff)^2);
% fprintf ('weighted attraction is %d \n',attraction);

for i=1:q
    x_right_diff(i)= ((table2(i,3)- table2(i,1))/768 * 100);
    y_right_diff(i)= (table2(i,4) - table2(i,2))/576 * 100;
    r_right_diff(i)= sqrt(x_right_diff(i).^2 + y_right_diff(i).^2);
    %r_right_inv(i) = 1/r_right_diff(i);
    dur_right(i) = table2(i,5);
end
x_right_diff = x_right_diff + 110;
% y_right_diff = (y_right_diff/576 * 100);
%a2 = mean(r_right_inv);
a2 = q * mean(dur_right)/sum(r_right_diff);
delta_a2 = sqrt((mean(dur_right)^2 + p^2 +
(mean(dur_right)^2+p^2)/sum(r_right_diff)^2)/sum(r_right_diff)^2);

for i=1:r
    x_left_diff(i)= ((table5(i,3) - table5(i,1))/768 * 100);
    y_left_diff(i)= (table5(i,4) - table5(i,2))/576 * 100;
    r_left_diff(i)= sqrt(x_left_diff(i).^2 + y_left_diff(i).^2);
    %r_left_inv(i) = 1/r_left_diff(i);
    dur_left(i) = table5(i,5);
end


%disp ([r_cen_diff' r_right_diff']);
x_left_diff = x_left_diff - 110;
% y_left_diff = (y_left_diff/576 * 100);
```

```
%a3 = mean(r_left_inv);
a3 = r*mean(dur_left)/sum(r_left_diff);
delta_a3 = sqrt((mean(dur_left)^2 + p^2 +
(mean(dur_left)^2+p^2)/sum(r_left_diff)^2)/sum(r_left_diff)^2);
% plot(x_cen_diff,y_cen_diff,'b*')
% hold on
% plot(x_right_diff,y_right_diff,'r+');
% hold on
% plot(x_left_diff,y_left_diff,'ys');
% hold on


end
```

……
……

Appendix C

Kinetic Analysis Code

```
function [startVal, endVal, normAfford, Ts] = FPonsetLookup (TLA)

rootname = 'C:\Users\Harsha\Documents\Mellina-lifting\Harsha-Melina - Lifting 2016\';
fname = dir(fullfile(rootname, '*FP_Data - onsets*.xlsx'));

datafile = fname.name;
s = importdata([rootname datafile]);

TLAindex = find(strcmp(TLA, s.textdata.Sheet1(:,1)));
startVal = s.data.Sheet1(TLAindex-1, 1);
endVal = s.data.Sheet1(TLAindex-1, 2);
normAfford = s.data.Sheet1(TLAindex-1,7);
Ts = s.data.Sheet1(TLAindex-1,9);

End
```

……………………………………………………………………………………………………

```
function affordance = AffordanceLookUp (TLA)

rootname = 'C:\Users\Harsha\Documents\Mellina-lifting\Harsha-Melina - Lifting 2016\';
fname = dir(fullfile(rootname, '*participantsAffordance*.xlsx'));

datafile = fname.name;
s = importdata([rootname datafile]);
%headers = s.textdata(1,:);

TLAindex = find(strcmp(TLA, s.textdata.Sheet1(:,1)));
affordance = s.data.Sheet1(TLAindex-1,7);


end
```

……………………………………………………………………………………………………
……………………………………………

```
clc
clear all
close all

rootname = ['C:\Users\Harsha\Documents\Mellina-lifting\Harsha-Melina - Lifting 2016\'];

fnames = dir(fullfile(rootname, '*CoP*.txt'));
finalArray = zeros(length(fnames), 13);
nameArray = cell(length(fnames),1);

for m = 1:length(fnames)
close all
```

```
dataFile = fnames(m).name;
CoPdata = importdata([rootname dataFile]);
CoPr = CoPdata(:,3);

TLA = fnames(m).name(1:5);
nameArray(m,1) = {TLA};
[startVal, endVal, normAfford, Ts] = FPonsetLookup(TLA);

absLift = CoPr(startVal:endVal);

targetSize = [101 1];
rbLift = imresize(absLift, targetSize);

plot(absLift, 'r');
figure;
plot(rbLift, 'g');

t = 0:1:100;
td = 1;
input = (normAfford*heaviside(t-td))';

results = iddata(rbLift, input, Ts);
sys = tfest(results, 5, 'Ts', Ts);

finalArray(m,:) = [sys.num sys.den sys.Ts sys.Report.Fit.FitPercent];

end

% prompt = {'Please enter the file name:', 'Please enter the starting value:', 'Please enter the end value:', 'Please enter the normalized affordance value:'};
% dlg_title = 'Input';
% num_lines = 1;
% defaultans = {'ASL_1CoP.txt','20','300','0.200'};
% answer = inputdlg(prompt,dlg_title,num_lines,defaultans);
%
% data = answer{1,1};
% G = str2double(answer{2,1});
% L = str2double(answer{3,1});
% affordance = str2double(answer{4,1});
%
% CoP = load(data);
% CoPr = CoP(:,3);
%
%
% % G = 138;
% % L = 346;
% abs_lift = CoPr(G:L);
% rb_lift = interpft(abs_lift,101);
%
%
% % figure
```

```
% % plot(abs_lift);
% figure
% plot(rb_lift);
%
%
% stepFunc = [zeros(1,1); affordance*ones(100,1)];
% %input function for system analysis
% inputFunc = stepFunc;
%
% outputFunc = rb_lift;
%
% assignin('base','input',inputFunc);
% assignin('base','output',outputFunc);
```

……………………………………………………………………………………………………

```
%This function calculates the start onset (G) and end onset (L), for
%individuals using the 'Load FP' data, specifically Mx data. Mx data is
%loaded from CalibrationEqns function and k is the number of indecies (6060)
function [G, L] = StartOnset (~,~)

k = 1;

while k ~= 0

prompt = {'Please enter the Calibrated file name:'};
dlg_title = 'Input';
num_lines = 1;
defaultans = {'ASL_1Calibrated.txt'};
answer = inputdlg(prompt,dlg_title,num_lines,defaultans);

%load the text data file
data = answer{1,1};
values = load(data);
Mx = values(:,4);
n = k;

% Build a low-pass filter
collection_frequency = 600; % Hz
[B A] = butter(2, 20 / collection_frequency / 2, 'low');    % 2nd order, 10 Hz

% Dual-pass filter the data (becomes a 4th order filter)
Mx_filtered = filtfilt(B, A, Mx); % this will return all NaNs if any value is NaN
Mx_edit = Mx_filtered;
Mx_edit2 = Mx_filtered;
Mx_edit3 = Mx_filtered;

% Use the first 100 frams (1000 ms) as the (hopefully) quiet baseline
Mx_mean = mean(Mx_filtered(1:100));
Mx_std = std(Mx_filtered(1:100));
```

```
% Find the first time each channel goes outside +/- 5 standard deviations
% (i.e. first fluctuation)
Mx_onset = min([ find(Mx_filtered > Mx_mean + 5*Mx_std, 1) find(Mx_filtered < Mx_mean -
5*Mx_std, 1) ]);
G = Mx_onset

Remove1 = (1:Mx_onset)';
Mx_edit(Remove1) = []; %indecies upto first onset value removed; Length of data array is
changed

%Find the second fluctuation point (value above +5 standard deviations)
next_onset = min(find(Mx_edit > Mx_mean + 5*Mx_std, 1));
%second onset value is equal to the first onset value plus the second
%fluctuating position. This is the Grasp onset (where the subjects touch the suitcase for the first
time)
Mx_onset2 = next_onset + Mx_onset;
L = Mx_onset2

Remove2 = (1:Mx_onset2)';
%indecies upto second onset point is removed; Length of the data array (i.e. Mx_edit) is
%changed again
Mx_edit2(Remove2) = [];

%Find the third fluctuation point (value less than -5 standard deviations)
third_onset = min(find(Mx_edit2 < Mx_mean - 5*Mx_std, 1));
%Thrid onset is the sum of previous two onset INDECIES and the last
%fluctuation indecies (due to changing data array length)
%Mx_onset3 = third_onset + Mx_onset2 + Mx_onset;
Mx_onset3 = third_onset + Mx_onset2;

Remove3 = (1:Mx_onset3)';
%Indecies upto third onset point is removed: Length of the data array (i.e.
%Mx_edit) is changed again
Mx_edit3(Remove3) = [];

%Find the fourth fluctuating point (i.e. value greater than +5 standard deviations)
fourth_onset = min(find(Mx_edit3 > Mx_mean + 5*Mx_std, 1));
%Final onset point is the sum of all three previous onset INDECIES and the
%index of the fourth fluctuating point
%End_onset = fourth_onset + third_onset + Mx_onset2 + Mx_onset
End_onset = fourth_onset + Mx_onset3;


figure;
%subplot(2,1,1), hold on, ylabel('Fx2');
%subplot(2,1,2),
hold on, ylabel('Mx (m)');
xlabel('Time (ms)');
title('Grasp & Lift Onsets');
%subplot(2,1,1), plot(Fx2_Fy2(:,1), 'c');
%subplot(2,1,2),
```

```
plot(Mx, 'm');
%subplot(2,1,1), plot(Fx2_Fy2_filtered(:,1), 'b');
%subplot(2,1,2),
plot(Mx_filtered, 'r');
%subplot(2,1,1), hline(Fx2_mean, 'k');
%subplot(2,1,2),
hline(Mx_mean, 'k');
%subplot(2,1,1), hline(Fx2_mean+5*Fx2_std, '--k');
%subplot(2,1,1), hline(Fx2_mean-5*Fx2_std, '--k');
%subplot(2,1,2),
hline(Mx_mean+5*Mx_std, '--k');
%subplot(2,1,2),
hline(Mx_mean-5*Mx_std, '--k');
%subplot(2,1,1), vline(Fx2_onset, 'g');
%subplot(2,1,2),
vline(Mx_onset, 'g');
vline(Mx_onset2, 'm');
vline(Mx_onset3, 'b');
vline(End_onset, 'g');

%return the two onset value indecies
% G = Mx_onset;
% L = LiftOnset + Mx_onset;

% Plot the two onset points over the Fy2 data
% figure;
% %subplot(2,1,1), hold on, ylabel('Fx2');
% %subplot(2,1,2),
% hold on, ylabel('Fy2 (m)');
% xlabel('Time (ms)');
% title('Grasp & Lift Onsets');
% %subplot(2,1,1), plot(Fx2_Fy2(:,1), 'c');
% %subplot(2,1,2),
% plot(Mx, 'm');
% %subplot(2,1,1), plot(Fx2_Fy2_filtered(:,1), 'b');
% %subplot(2,1,2),
% plot(Mx_filtered, 'r');
% %subplot(2,1,1), hline(Fx2_mean, 'k');
% %subplot(2,1,2),
% hline(Mx_mean, 'k');
% %subplot(2,1,1), hline(Fx2_mean+5*Fx2_std, '--k');
% %subplot(2,1,1), hline(Fx2_mean-5*Fx2_std, '--k');
% %subplot(2,1,2),
% hline(Mx_mean+5*Mx_std, '--k');
% %subplot(2,1,2),
% hline(Mx_mean-5*Mx_std, '--k');
% %subplot(2,1,1), vline(Fx2_onset, 'g');
% %subplot(2,1,2),
% vline(Mx_onset, 'g');
% vline(LiftOnset+Mx_onset, 'y');
% %vline(fmax_index,'b');
```

```
prompt2 = {'Enter 0 to exit, 1 to continue:'};
dlg_title2 = 'Exit Info';
num_lines2 = 1;
defaultans2 = {'1'};
answer2 = inputdlg(prompt2,dlg_title2,num_lines2,defaultans2);

k = str2double(answer2{1,1});

end


end
```
………

```
function [inputFunc, rbTotal2] = CalibrateSignals (~,~)

k = 1;

while k ~= 0

prompt = {'Please enter the file name:', 'Please enter the affordance distance:'};
dlg_title = 'Input';
num_lines = 1;
defaultans = {'ASL_1.txt','20'};
answer = inputdlg(prompt,dlg_title,num_lines,defaultans);

%data = input(prompt,'s');
data = answer{1,1};

%save the input file name
[~,name,~] = fileparts(data);
fname = [name,'Calibrated.txt'];

fname2 = [name,'CoP.txt'];

%load data from text file
values = load(data);

%break into separate arrays; changed column numbers according to the second
%experiments' data sets, i.e. columns 3 to 8 and only 1 forceplate (Sep 22,2016)
Fx_1 = values(:,3);
Fy_1 = values (:,4);
Fz_1 = values(:,5);
Mx_1 = values(:,6);
My_1 = values(:,7);
Mz_1 = values(:,8);
% Fx_2 = values(:,7);
% Fy_2 = values(:,8);

n = length(Fx_1);
```

```
%matirx A represents the force plate #1 data
A = [Fx_1 Fy_1 Fz_1 Mx_1 My_1 Mz_1];
%divide by 5 to get rid of the external gain
A_noGain = A/5;

%calibration matrix for force plate #1
CaliMatrix = [1260.6 28.1 2.2 4.8 -6.8 5.1; -50.7 1254.0 -2.3 -2.1 -10.6 4.7; 3.5 -3.0 1881.4 8.2 -
5.7 9.7; 2.9 -55.7 -2.3 583.8 -0.3 0.8; 53.8 2.9 -0.4 -1.3 408.1 0.8; 2.6 -3.6 -3.3 -0.3 -0.6 291.4];
%take transpose for matrix multiplication purposes
B = CaliMatrix.';

%matrix multiplication, Matrix C is the resultant (calibrated resultant) matrix
for i=1:n
   C = A_noGain*B;
end
%take transpose of C to be used for fileID function
D = C';

%write the matrix D into a .txt file
fileID =  fopen (fname,'w');
fprintf(fileID,'%8.5f %8.5f %8.5f %8.5f %8.5f %8.5f\r\n',D);
fclose(fileID);

% Build a low-pass filter
collection_frequency = 600; % Hz
[B, A] = butter(2, 20 / collection_frequency / 2, 'low');    % 2nd order, 10 Hz

C_filtered = zeros(6060,6);
for k = 1:6
   % Dual-pass filter the data (becomes a 4th order filter)
   C_filtered(:,k) = filtfilt(B, A, C(:,k)); % this will return all NaNs if any value is NaN
end

%COPx (centre of pressure in x-direction) = My/Fz and writting to txt file
COPx = -1*( C_filtered(:,5)./C_filtered(:,3));
COPy = (C_filtered(:,4)./C_filtered(:,3));
COPr = sqrt(COPx.^2 + COPy.^2);

COP_all = [COPx COPy COPr];
E = COP_all';

fileID2 = fopen(fname2, 'w');
fprintf(fileID2, '%8.5f %8.5f %8.5f\r\n', E);
fclose(fileID2);

prompt2 = {'Enter 0 to exit, 1 to continue:'};
dlg_title2 = 'Exit Info';
num_lines2 = 1;
defaultans2 = {'1'};
answer2 = inputdlg(prompt2,dlg_title2,num_lines2,defaultans2);
```

```
k = str2double(answer2{1,1});
end

end
```
…………………………………………………………………………………………………

```
%this function takes in the Fz data from the stance FP and finds the 'local
%minimum' value just before it goes down to the baseline value. 'Local
%minimum' represents the point when the participant's force in Z direction
%is in free-flow which indicates the end of the lift
function [EoL] = EndofLift (data)

%load data from text file
values = load(data);

%break into separate arrays
Fx_1 = values(:,1);
Fy_1 = values (:,2);
Fz_1 = values(:,3);
Mx_1 = values(:,4);
My_1 = values(:,5);
Mz_1 = values(:,6);
Fx_2 = values(:,7);
Fy_2 = values(:,8);

n = length(Fx_1);
%matirx A represents the force plate #1 data
A = [Fx_1 Fy_1 Fz_1 Mx_1 My_1 Mz_1];
%divide by 5 to get rid of the external gain
A_noGain = A/5;

%calibration matrix for force plate #1
CaliMatrix = [1260.6 28.1 2.2 4.8 -6.8 5.1; -50.7 1254.0 -2.3 -2.1 -10.6 4.7; 3.5 -3.0 1881.4 8.2 -
5.7 9.7; 2.9 -55.7 -2.3 583.8 -0.3 0.8; 53.8 2.9 -0.4 -1.3 408.1 0.8; 2.6 -3.6 -3.3 -0.3 -0.6 291.4];
%take transpose for matrix multiplication purposes
B = CaliMatrix.';

%matrix multiplication, Matrix C is the resultant (calibrated resultant) matrix
for i=1:n
   C = A_noGain*B;
end
%take transpose of C to be used for fileID function
D = C';

[Gon , Lon] = GraspOnset (Fy_2, n);

%call function Fz_min_local
Fz_min_local = FzMinimum (C(:,3), Lon);
EoL = Fz_min_local;

display(Fz_min_local);
```

end
………………………………………………………………………………………………..............