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**The Effect of Posture Category Salience on Decision Time and Errors when Using
Video-Based Posture Assessment Methods**

by

Kryisia Montero-Fiedler

A Thesis

Submitted to the Faculty of Graduate Studies
through the Faculty of Human Kinetics
in Partial Fulfillment of the Requirements for
the Degree of Master of Human Kinetics at the
University of Windsor

Windsor, Ontario, Canada

2010

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ABSTRACT

Video-based posture assessment methods require classification of body postures into categories, a visual search task that can be improved by introducing salience in the search field. The purpose of this study was to investigate the effect that posture category salience (borders, shading and colour) had on error rates and decision times. Ninety participants were instructed to select posture categories in five salience conditions (no salience (plain), grey and red borders, and grey and red shading) as quickly and accurately as possible, for images presented on a computer interface. Participants responded quickest in the border conditions, with classification times about 5% lower than the plain condition. The coloured diagrams significantly reduced classification errors by approximately 1.5%. Participants perceived the colour conditions to be the easiest and fastest to classify and to lead to the fewest classification errors. Incorporating a grey border can improve users' performance by reducing errors and decision times.

DEDICATION

To my husband, Christian and my children, Inés and Jan, who embellish my life and
make worthwhile every effort and achievement in my journey.

To my siblings Katia and Mario who have been sources of inspiration in my
development.

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GLOSSARY

Achromatic – Perceived colour that contains no hue, it is defined by its lightness in the grayscale (from white to black).

Asymmetry – Differences between objects due to the presence or absence of a feature.

Background – The part of a scene that appears to be farthest from the viewer.

Biomechanical Load – Force that is applied to a tissue.

Biomechanics – The study of the mechanical principles in living organisms.

Characteristic – An attribute of an object.

CIELAB – A system presented by the Commission Internationale d'Eclairage (CIE)/ International Commission on Illumination with the components of Lightness and A and B colour axes (LAB). An opponent colour system based on colour stimuli that are translated into distinctions between light and dark, red and green, and blue and yellow. The system presents a spatial location of the colours with coordinates in XYZ in relation to a defined white point for its reproducibility.

Crease – A slight depression (concavity) in the smoothness of a surface.

Cumulative Load – Accumulation of biomechanical load on a tissue over time.

Distractor – An object in the visual field that is not the target object.

Feature – The dimensional value (discrete or categorical) of a characteristic defining an object, such as “red” in the characteristic of colour.

Foreground – The part of a scene that is nearest to and in front of the spectator.

Goniometer – An instrument that measures angles or segment postures.

Human-Computer Interaction – The communication between a person and a computerized device through an interface.

Hue – One of the three components of colour, usually perceived as the combination of one or more of the basic opponent hue channels: yellow-blue and red-green. The other two components are lightness and colourfulness.

Interface – A machine device or computer program with which people interact with a computer system, allowing input from the human user and output from the computer system.

Visual Interface – The visual elements, including the computer screen display, which allow the interaction between a person and the computer system.

Lumbar – Pertaining to the region created by the lumbar vertebrae, L1 to L5 (low back), between the diaphragm and the pelvis.

Luminance – The measure of the light intensity emitted or reflected by an object.

Musculoskeletal Disorders – Damage to any component of the musculoskeletal system that occurs gradually or chronically.

Bursitis – Inflammation of bursa of joints due to repetitive movements.

Carpal tunnel syndrome – A condition caused by the compression of the median nerve because of increased pressure between the carpal bones and the transverse carpal ligament of the wrist.

Epicondylitis – Inflammation of the elbow's lateral or medial epicondyle.

Myalgia – Pain in one or multiple muscles.

Sprain – An injury to a ligament caused by exceeding the tissue's tolerance.

Strain – An injury to a muscle caused by exceeding the tissue's tolerance.

Tendonitis – Inflammation of the shoulder, elbow or wrist joint due to microtears of the tendon.

Tenosynovitis – Inflammation of the lining of the synovial sheath that surrounds a tendon.

Musculoskeletal System – The system that includes muscles, bones, joints, tendons, ligaments, and their corresponding nerves and blood vessels, working together to generate movement. It provides support and protection to the brain and internal organs, and participates in blood cell and mineral formation, and storage of minerals and fat.

Object – A two- or three- dimensional entity.

Peak Load – The biomechanical load to a tissue that has the largest magnitude in a cycle.

Posture – Angular position of a body part in relation to the vertical (trunk) or to other body part (arm, forearm).

Posture Category – The graphic description of a section of angles involved in the movement range of a body segment.

Protrusion – A projection of one part of an object.

Sagittal Plane – An imaginary longitudinal surface that divides the human body into right and left sections, and describes movements that happen in a forward or backward fashion such as trunk flexion or extension.

Salience – The quality of an object that stands out relative to neighboring objects.

Shading – The transparency assigned to one of two overlapping objects visually positioned closer to the viewer.

Shape – The geometrical definition of an object.

Symmetry – Similarities between objects due to the presence of the same feature.

Target Object – An object toward which the visual attention is directed.

Visual Search – The perceptual task of looking for objects in the visual field.

Parallel visual search – A perceptual appreciation of all the elements in the visual field performed at the same time.

Serial visual search – The perception of each object in the visual field, one at a time.

Chapter I

INTRODUCTION

Musculoskeletal disorders (MSDs) are the single largest cause of absenteeism from work in Canada and many other countries (Punnett & Wegman, 2004), and accounted for more than half of the work-related health claims among all industries in Ontario in 2007 (WSIB, 2008). MSDs involve damage to one or more of the components of the musculoskeletal system, such as muscles, joints, ligaments and tendons, and are not typically the result of an instantaneous or acute event, but are due to gradual or chronic damage caused over a period of time (Garg & Kapellusch, 2009; Punnett & Wegman, 2004). The low back has been the focus of many research studies because it has exhibited the largest number of reports of work-related injuries and illnesses in the last two decades in the United States (U.S. Bureau of Labor Statistics, 2007) and Canada (WSIB, 2008).

Researchers have linked rapid work pace, repetitive motion patterns, forceful exertions, excessive biomechanical loading of musculoskeletal tissues and body postural stress to the development of MSDs (Garg & Kapellusch, 2009; Punnett & Wegman, 2004; Norman et al., 1998; Punnett et al., 1991). Loading of the musculoskeletal structures can lead to tissue deformation and failure, if the tissue's tolerance is exceeded (Kumar, 1990). Therefore, the quantification and analysis of physical stress on body tissues at specific instants (peak loading) during cycles of occupational tasks and the accumulation of tissue loading over a period of time (cumulative loading), are imperative

actions in the prevention of the onset and further development of work-related MSDs (Garg & Kapellusch, 2009; Punnett & Wegman, 2004; Punnett et al., 1991).

The calculation of peak and cumulative tissue loading using biomechanical models requires the description of the body segments involved in the person's posture (Winter, 2005). Different approaches have been implemented to assess and measure working postures in industrial and field settings, ranging from direct observation of the work tasks with manual recording of estimated loads, time and posture angles on paper (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993), to direct measurements of working loads and digitization of movements with computerized systems (Callaghan et al., 2005; Juul-Kristensen et al., 1997; de Looze et al., 1994; Marras et al., 1993).

Direct observation methods are easy to implement in industry, not very invasive for the physical movements of the observed worker and do not require extensive training for the analyst, but can not offer detailed data for accurate quantification of biomechanical loads (Juul-Kristensen et al., 1997; de Looze et al., 1994). Conversely, direct measurement approaches are able to generate very accurate data for detailed risk analyses of occupational activities but are very costly due to the required equipment and analyst training. They can also be intrusive for the assessed workers, interfering with their performance when implemented in the field. Consequently, direct measures are generally more suitable for lab settings (Juul-Kristensen et al., 1997; Marras et al., 1993). In addition, biomechanical models involved in the calculation of peak and cumulative loads associated with working postures are determinant for having an accurate representation of the evaluated tasks. Although three-dimensional (3D) dynamic models are ideal for calculating loads present in dynamic industrial tasks involving 3D trunk

motion, the evaluation of the data generated is time consuming and complex, making the process inefficient (Callaghan et al., 2005; Marras et al., 1993). Video-based posture assessment methods have the advantage of not interfering physically with the activities that the workers perform during their occupational duties (Jäger et al., 2000), while providing a visual record that can be analyzed at a later time (Andrews & Callaghan, 2003; Keyserling, 1986). The postures involved in the tasks can be observed on video in static frames and described using different approaches: posture digitization (Norman et al., 1998), posture classification, either using paper diagrams (Lowe, 2004; Hignett & McAtamney, 2000; McAtamney & Corlett, 1993) or using computer interfaces (Callaghan et al., 2003; Jäger et al., 2000).

A video-based posture assessment method called 3DMatch was developed for the purpose of assessing peak and cumulative loads at the joints, combining the characteristics of checklist methods for assessing postures and a 3D biomechanical model (Callaghan et al., 2003). This approach provides the possibility of extracting 3D characteristics of trunk, neck, shoulder and elbow movements using a two dimensional (2D) posture classification method by observing still frame sequences from video records of work tasks and classifying the postures into the categories which best represent them. This makes the process of posture assessment more efficient and easier to implement with simple training protocols (Andrews et al., 2008b; Weir et al., 2006; Callaghan et al., 2003).

Many studies have evaluated the functionality and efficiency of video-based approaches that involve posture categorization. The evaluation has focused on the sensitivity of the users in visualizing and correctly describing postures based on the

displayed categories and the impact of posture misclassification (van Wyk et al., 2009; Andrews et al., 2008a; Andrews et al., 2008b; Weir et al., 2007; Arnold, 2005; Lowe, 2004). However, the properties of the graphic presentation of the posture categories, as an element to improve the sensitivity of the analyst, have not yet been explored.

Video-based posture assessment methods such as 3DMatch require the use of human-computer interfaces in which the posture to be analyzed and the posture categories are displayed on a computer screen as the tool to perform the assessment. Therefore, the characteristics of visual search applied to human-computer interaction (HCI) are relevant and need to be evaluated if improved posture classifications are to be realized.

Computer interfaces involve the visual identification of target objects in the 2D display and the discrimination of other objects that are not relevant for the desired task (Michalski & Grobelny, 2008). Some objects are detected more easily due to their asymmetry with other interacting objects in a visual display (Treisman & Gormican, 1988). This asymmetry generates salience and allows for an effective use of an interface if the salience is related to the task's target object (Michalski & Grobelny, 2008; Bodrogi, 2003). In the interface used for posture classification, the task is to visualize the posture categories that need to be compared for the assessment of work postures. The angle range that defines the categories must be salient in the displayed diagram in order to be quickly identified for the visual comparison of observed postures and the available classification categories. The current study will evaluate the salience of posture categories in the visual interface of video-based posture assessment methods such as 3DMatch (Callaghan et al., 2003).

1.1. Statement of Purposes

This study investigated factors related to (1) the identification of the posture category range, and (2) the visualization of the posture category boundaries, which define the classification categories in video-based posture assessment methods. The purpose of this study was to determine the effect of different salience conditions on the performance of analysts classifying postures using graphic posture categories. Performance was assessed by registering the time required to complete the classification task (decision time) and the accuracy (error rate) in selecting posture categories via a computer interface.

The salience conditions analyzed in this study were: posture categories as closed objects delimited by achromatic (grey) borders (GB); achromatic shading of the posture categories (GS); and the presence of colour (red) in the posture category borders (RB) and in the shaded posture categories (RS).

1.2. Statement of Hypotheses

It was hypothesized that:

i) Showing the posture category as a closed object and shading the area defining the posture category will reduce the decision time and the number of classification errors made by analysts, compared to their performance using the current 3DMatch visual display.

ii) Shading will reduce the decision time and number of classification errors to a greater extent than showing the posture categories as closed objects without shading.

iii) Colour borders and shaded posture categories will reduce the decision time and the number of classification errors to a greater extent, compared to the same non-colour conditions.

iv) The effect that the salience conditions have on decision time and number of errors is the same when selecting a posture category for classifying trunk, shoulder flexion and extension postures, or elbow flexion postures.

v) Female and male analysts perform equally in regards to decision time and number of classification errors when selecting postures categories with different salience conditions.

Chapter II

LITERATURE REVIEW

2.1. Occupational Loading of Tissues

Musculoskeletal disorders (MSDs) are considered to result from damage to one or more of the components of the musculoskeletal system, such as muscles, joints, ligaments, tendons, peripheral nerves and blood vessels. MSDs commonly occur gradually from causal events over an extended period of time, but can also occur as a result of a single overexertion event such as lifting, lowering, pushing or pulling. The mechanisms of injury to musculoskeletal tissues are not yet fully understood, but some occupational conditions, such as repetitive or forceful manual exertions, rapid work pace, insufficient recovery time and dynamic and static non-neutral postures, have been identified as risk factors for the onset of MSDs (Garg & Kapellusch, 2009; Punnett & Wegmann, 2004).

MSDs accounted for 53% of workers' total lost time claims among all industries in Ontario in 2007. MSDs represented by sprains, strains, and clinical syndromes such as tenosynovitis, epicondylitis, bursitis, carpal tunnel syndrome, myalgia, and low back pain (Punnett & Wegman, 2004), impact workers' health and safety significantly and place a huge economic burden on the province (WSIB, 2008). The body parts most commonly affected are the low back, neck, shoulder, forearm, and hand (Village et al., 2005; Punnett & Wegman, 2004), with the low back exhibiting the largest number of reports (21%) of work-related injuries and illnesses (WSIB, 2008).

Biomechanical stress on tissues of the musculoskeletal system has been linked to the development of MSDs (Punnett & Wegman, 2004; Norman et al., 1998; Punnett et

al., 1991; Kumar, 1990) and is caused by external loads and their corresponding reaction forces (Winter, 2005; Norman et al., 1998). These stresses can occur at specific instants (peak loading) during cycles of occupational tasks or over time (cumulative loading). Tissues can be injured when the loads applied to them exceed the tissue's tolerance (Kumar, 1993).

Several guidelines have been published regarding force tolerance limits to prevent tissue damage (Waters et al., 1993; Mital et al., 1993; Snook & Ciriello, 1991). The National Institute for Occupational Safety and Health (NIOSH) established a maximum compression force limit of 3400 N on the spine to prevent tissue damage. This limit was estimated based on field studies that linked the incidence of low back pain (LBP) in industrial workers and manual exertion (carrying, lifting, pushing, pulling) that cause compression force on the spine above 3400 N (Waters et al., 1993). Maximum acceptable weight of lift (MAWL) and maximum acceptable limits for push and pull forces at different heights, frequencies and distances were recommended by Snook & Ciriello (1991) based on psychophysical force tolerance perception expressed by industrial workers. Their guidelines express the force in kilograms for males and females to exert at the hands at heights from 25 to 135 centimetres. The frequencies varied from once every six seconds to once every eight hours and distances from 2 to 60 metres for push/pull tasks. However, most of these guidelines refer to limits calculated for manual material handling activities using postures with variations in the sagittal plane only (Marras et al., 1993). Mital and colleagues (1993) developed guidance limits for lifting, lowering, carrying, pushing and pulling obtained by the psychophysical estimations data of Snook and Ciriello (1991), providing several adjustments that would impact the force exertion

limits, such as working duration, asymmetrical lifting/lowering and load asymmetry. Marras and colleagues (1993) stressed the importance of the use of three-dimensional (3D) posture inputs and trunk kinematics when assessing biomechanical loads of the spine to accurately determine the risk of developing LBP. Since most industrial tasks involve 3D trunk motion (Marras et al., 1993), the calculation of biomechanical loading for any occupational task should be performed using 3D biomechanical models (Callaghan et al., 2003).

Some studies have shown that biomechanical stress on the low back in automotive workers occurred even in tasks not involving any manual exertion (Norman et al., 1998; Punnett et al., 1991). Other studies have also focused on the assessment of postural stress to the trunk and upper limbs, pointing out the relationship between the performance of occupational activities in non-neutral postures and the increased incidence of injuries (Keyserling, 1986). An increased risk of injury due to biomechanical stress may be caused when the body holds positions differing from a neutral posture, for example, prolonged forward trunk flexion, trunk torsion or prolonged elevation of the arms above the shoulders (Punnett & Wegman, 2004; Norman et al., 1998; Punnett et al., 1991; Keyserling, 1986). A neutral posture is defined by Keyserling (1986) as a posture in which the trunk is extended, flexed, laterally bent or rotated not more than 20 degrees from the upright vertical position and the arms flexed or abducted less than 45 degrees from the trunk. Arnold (2005), however, defined a neutral posture with more narrow parameters, with the arms within a range of -20 to +20 degrees from anatomical position, and the trunk within a range from 15 degrees of extension to 15 degrees of flexion, and less than 15 degrees of lateral bending.

2.1.1. Peak and Cumulative Loading Assessment

Extensive research has been performed regarding the assessment of peak and cumulative loading of the musculoskeletal system, primarily focused on the spine (Callaghan et al., 2005; Callaghan et al., 2001; Jäger et al., 2000; Norman et al., 1998; Kumar, 1990), and the spine and shoulder (Cann et al., 2008; Village et al., 2005) in different occupational settings. The peak load on a tissue is usually assessed by the identification of the largest load experienced in a cycle or task, while cumulative loading requires the calculation of loads over a period of time and extrapolation to the total load exposure or for the duration of the task or during a work shift (Callaghan et al., 2001; Norman et al., 1998). To obtain the peak biomechanical loads in a task requires the calculation of force at an instant, but for the quantification of cumulative biomechanical loading, it is necessary to document the variations of the task over time (Callaghan et al., 2001). In addition to the recording of the amount and direction of the external load applied to the body (i.e. the weight of an object carried with the hands), and the position of the load with respect to the body (point of application of the exerted force), the calculation of peak and cumulative loads requires the position of relevant body segments in space (Winter, 2005). In other words, the accurate calculation of biomechanical loads experienced while performing a task is directly related to the accurate assessment of body postures.

Kumar (1990) evaluated cumulative load using posture data collected in two-dimensional (2D) representations of recalled postures of tasks by nursing aides. The analyzed workers identified in questionnaires the most commonly used static postures. The initial and final postures for dynamic segments of tasks, external loads, and height

and weight were also provided. The dynamic variations of the task segments were simulated from the initial to the final posture in a smooth and continuous way. These data were used as input for a biomechanical model to calculate the compression and shear forces at the thoracolumbar and the sacrolumbar joints in the spine for static postures at 200 milliseconds intervals. The total cumulative values for the static postures were obtained by multiplying the biomechanical loads by the duration of the tasks; and for the dynamic tasks, by the summation of the products of the average load by time intervals of each segment.

Jäger and colleagues (2000) evaluated the compression and shear forces, and flexion and torsional moments at the lumbosacral (L5/S1) joint of workers performing their regular activities in surface construction, meat- and metal-processing, and during waste collection: activities identified as presenting intense lumbar stress. Postural data obtained from in-field work videotape, together with the measured weights handled and individual worker anthropometrics were input into a 30 segment biomechanical model to calculate the above mentioned loads at registered instants. The instants were added in continuous sequences for each video to determine the loads over an entire shift.

Peak and cumulative loading has also been calculated at the L4/L5 joint of automotive workers of an assembly facility (Norman et al, 1998). Peak compression and shear forces, and peak moments were evaluated at instants identified as having substantial loading. The cumulative values were obtained by multiplying each task peak compression instants by the duration of the exposure in each task and the number of times that the task was performed during the shift.

The differences in the calculation of cumulative tissue loading are not only reflected in the procedure used for the summation of the total loads, but also in the biomechanical model used to calculate the loads at each individual posture. Dynamic (Callaghan et al., 2001), quasi-dynamic (Norman et al., 1998) and static (Callaghan et al., 2003; Jäger et al., 2000; Kumar, 1990) biomechanical models have all been used in the calculation of cumulative low back loads. Naturally, the dynamic model provides the biomechanical loads experienced by a person during occupational tasks with more accuracy (compared to the actual loads) than the quasi-dynamic and the static models, but also requires more detailed data collection, resulting in greater cost for the evaluation (Jäger et al., 2000) and larger data processing time (Callaghan et al., 2001).

Callaghan and colleagues (2001) evaluated differences in the cumulative load (compression, joint shear, reaction shear, and flexion/extension moment) values at the L4/L5 joint for the same task obtained from a dynamic, a quasi-dynamic and a static biomechanical model. The dynamic model included linear and angular acceleration of the weights at the hands and body segments, the quasi-dynamic model included acceleration of the hand loads but not of the body segments and the static model did not include any acceleration of the hand loads or segments. The study showed that the average error in the calculation of spine loads from the quasi-dynamic and static models was less than 2.76%, and less than 12.55%, respectively, compared to the dynamic model. These results suggest that the use of either a quasi-dynamic or static model will be a reasonable substitute for a full dynamic model and have the advantage of reducing data collection and processing time as well as costs.

2.2. Postural Analyses

Biomechanical analyses using biomechanical models typically require the input of the loads acting on the body, the direction and acceleration of the forces acting on tissues, and the description of segment postures. Different methods have been used for the purpose of describing working postures for these analyses (Callaghan et al., 2003; Jäger et al., 2000; Juul-Kristensen et al., 1997; Kumar, 1990; Keyserling, 1986), and to identify postures which can lead to mechanical stress (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993; Punnett et al., 1991). Some of these methods include questionnaires (Kumar, 1990), electrogoniometers (Juul-Kristensen et al., 1997; Marras et al., 1993), motion tracking optoelectronic systems (de Looze et al., 1994), direct observation using checklists (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993), and video-based methods (Callaghan et al., 2003; Jäger et al., 2000; Norman et al., 1998; Keyserling, 1986).

Self-reported evaluations of postures through 2D drawings presented in questionnaires was an approach used to collect data of workers from social and health services, providing the possibility of gathering a large amount of posture data at low monetary cost. The analysis was effective at evaluating 161 participants which allowed for the calculation of cumulative loading on the spine and estimation of LBP in a large population with suspected risk of MSDs (Kumar, 1990). One limitation of this approach is that it relies on the subjectivity of the participants in the study.

Direct posture measurements using movement-activated electrogoniometers are an effective method to track body kinematics such as lateral and torsional displacement and acceleration. Electrogoniometers can be attached to body segments in order to

measure body angles, eliminating the visual estimation of the analyst (Juul-Kristensen et al., 1997). However, they are more suitable for lab settings due to the electronic instrumentation required. A lumbar motion monitor was used to assess the 3D position of the thoracolumbar spine outside the lab setting, evaluating 403 jobs related to repetitive manual material handling in industrial manufacturing plants (Marras et al., 1993). The tracking of spine posture over a period of time serves to describe the posture for input into dynamic biomechanical models or to identify movements as factors for the development of LBP. It has been observed that increased trunk motion during lifting could accentuate spine loading due to the reaction forces generated by the musculoskeletal system (Marras et al., 1993).

Optoelectronic systems, which require the attachment of reflective markers at different joints to the person, can also be used to assess posture. Different body postures used while performing a task are electronically recorded along with the exposure time for each posture. The obtained 3D posture coordinates are very accurate, but they are limited to the evaluation of few subjects and generally in lab settings (de Looze et al., 1994).

Direct measurement methods generally provide very accurate and precise values for the analyzed posture, but are difficult to implement in work settings due to the required instrumentation and limited equipment mobility (Lowe, 2004; Callaghan et al., 2003; Juul-Kristensen et al., 1997; de Looze et al., 1994). Such methods are also very time consuming because of the extensive data generated (Callaghan et al., 2003). Conversely, direct observation of workstations is easy to implement and requires inexpensive equipment. The worker's posture is usually documented on paper using a posture scale ranging from neutral to extreme, or by using categories (Lowe,

2004; Hignett & McAtamney, 2000; McAtamney & Corlett, 1993). This type of documentation may be simple to use but can produce very variable data when relying on the perception of analysts during the assessment of work postures in real time (Callaghan et al., 2005; Juul-Kristensen et al., 1997; Keyserling, 1986). de Looze and colleagues (1994) compared the direct measuring of postures involved in experimental dynamic tasks using an optoelectronic system to the postural records obtained from observations of the same tasks. Participants in the experiment simulated simple manual material handling tasks in the lab. A computerized system captured postures from the sagittal view, recording the coordinates of light-reflecting markers attached to the neck, shoulder, elbow, low back, hip, knee and ankle of the observed subjects. Simultaneously, two analysts observed the tasks in the same sagittal view, classifying the variations in postures and the handled loads by pressing keys on a computer keyboard. They found that the observational method resulted in a high error rate in the identification of postures, even when the observational conditions were optimized. During direct observations, the analyst must accomplish a complex task, perceiving all postural aspects presented in an instant and record them (de Looze et al., 1994). Therefore, direct observation is a recommended method to evaluate static postures or tasks with little variation.

Two direct observation approaches, RULA (Rapid Upper Limbs Assessment) designed by McAtamney and Corlett (1993), and REBA (Rapid Entire Body Assessment) designed by Hignett and McAtamney (2000), utilize simplified systems of numerical grades to represent the postures, in order to detect musculoskeletal stress at the neck, trunk, shoulders, elbows, and wrists (RULA), and all body segments (REBA). The analyst obtains a posture score for each segment by adding scores given to different

angles of flexion and extension at each body segment, to deviations in the frontal plane and to the ranges of applied forces. The overall score is compared in a table to determine if the posture is acceptable, if it requires further investigation, or prompt or immediate changes. REBA also uses scores for exerted forces and working pace and introduces the score for hand coupling as a component in the handling of loads (Hignett & McAtamney, 2000). Both REBA and RULA combine graphic and written descriptions of postures to present classification categories. 2D diagrams depicting flexion/extension angle of movement for the neck, trunk, shoulder, elbow and wrists are shown in the evaluation sheets of RULA and REBA, and flexion/extension of the knee in those of REBA. The category sizes for mild and severe trunk flexion postures in RULA and REBA are larger than the ones used by Keyserling (1986) and Punnett and colleagues (1991), with categories of 40 and 60 degrees, respectively. The neutral posture, however, is defined in a smaller range between 0 to 20 degrees, while trunk extension ranges from 0 to -10 degrees. RULA and REBA are more detailed for arm flexion/extension, having five categories (>-15 degrees, <-15 to >15 degrees, >15 to <45 degrees, >45 to <90 degrees and >90 degrees), compared to three categories of combined arm flexion/abduction in the system by Keyserling (1986). Other descriptions related to trunk lateral bending and rotation, and shoulder and wrist abduction/adduction are presented only in written form in RULA and REBA, with a score to indicate if they are present or not (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993).

2.2.1. The Use of Video-Based Methods

Video recording as an observational method for all occupational tasks provides the advantage of having reduced physical interference for the worker, allowing the regular development of his/her job tasks relatively undisturbed (de Looze et al., 1994). Video also generates a visual record, which can be used for postural analysis at a later time (Andrews & Callaghan, 2003; Keyserling, 1986), offering advantages for the analyst who can replay the videotape to assess the posture of different body segments, one by one (Keyserling, 1986).

Jäger and colleagues (2000) used a video-based approach for their occupational field analysis. The activities were video recorded in the working settings and analyzed in the lab. The analysts observed the tasks in the videotape and classified the working postures and hand loads using a numerical code system, with values for different postures and forces. The description of each specific posture was contained in a single code used as input into a quasi-dynamic biomechanical model for the calculation of the loads at the lumbar spine (Jäger et al., 2000).

Norman and colleagues (1998) used video to document task cycles performed by automotive workers. Trained analysts directly observed workers at their working facility and identified instants of substantial loading to the spine in the tasks. They manually documented trunk postures, measured the magnitude and direction of forces on the hands, and the duration and repetition of peak efforts. From the video, the analysts obtained a frame representing the instant of peak loading and digitized the posture for input into a biomechanical model. The posture data and the recorded hand force values were used to calculate the peak spine loads in a cycle, extrapolating those loads for the calculation of

cumulative loading over the complete shift. However, the posture assessment was limited to the sagittal plane, leaving aside trunk lateral bending and torsion; possible factors contributing to additional postural stress (Norman et al., 1998; Marras et al., 1993).

Similar to RULA and REBA (Hignett & McAtamney, 2000; McAtamney & Corlett, 1993), which use direct observation of tasks and posture classification on paper checklists, posture categories can also be used to describe and quantify working postures captured on video (Callaghan et al., 2003; Keyserling, 1986). Keyserling (1986) developed a classification system, combined with the use of video recordings, for describing trunk and shoulder postures. The analysts using this approach were able to observe a working cycle multiple times on video, played in real time, in order to quantify trunk flexion or extension, lateral bending and rotation, and shoulder flexion and abduction, relative to the trunk. The main objective of Keyserling's system was to identify non-neutral postures in occupational tasks and the degree of deviation from neutral postures (i.e. whether it was mild or severe).

A video-based posture assessment method, 3DMatch, was developed for the purpose of assessing peak and cumulative loads on the spine and shoulders through an evaluation of videotaped samples of occupational tasks (Callaghan et al., 2003). The method involves the classification of 3D postures present in dynamic tasks, shown in still frames, into posture categories displayed on a computer interface. A video clip of a posture is shown frame by frame on the upper left portion of the screen with a set of posture categories representing different views of body segments below (Figure 1). A section for the input of anthropometric values (mass and height) of the person in the video clip is provided on the upper right part of the screen. Each body segment (trunk,

neck, arm and forearm) posture is classified in 2D views of flexion/extension, lateral bend and axial rotation to provide the 3D description of the overall posture at every frame. The coordinates of the body joints describing the posture and the anthropometric data of the person that is being analyzed are inputted into a 3D rigid segment biomechanical model. The static model programmed in the 3DMatch software uses the location of the evaluated body segments, body mass distribution and the loads at the hands to calculate the peak forces and moments acting on the elbow, shoulder, C7/T1 and L4/L5 joints. The cumulative load on the low back is calculated by integration of each frame of data for the duration of the exposure obtained from the video clip of the task. The 3DMatch model output displays on the interface screen the peak and cumulative loads at the L4/L5 joint for each evaluated task, compared to load tolerance limits. Expanded information, shown in model files that are viewable via spread sheets, provides the frame by frame peak loading, cumulative loading and amount of time spent in each posture range (neutral, moderate and severe). The analyst using 3DMatch can use this information for the estimation of risks in the development of MSDs in areas such as the low back (Callaghan et al., 2003).

The use of 3DMatch for analyses performed in industrial settings has the advantage of requiring little in the way of equipment investment: only a video camera and standard computer are necessary to use the software. Additionally, the mobility of the equipment allows for performing assessments at various occupational settings (Callaghan et al., 2003) such as hospitals, construction sites, food services or industrial assembly lines.

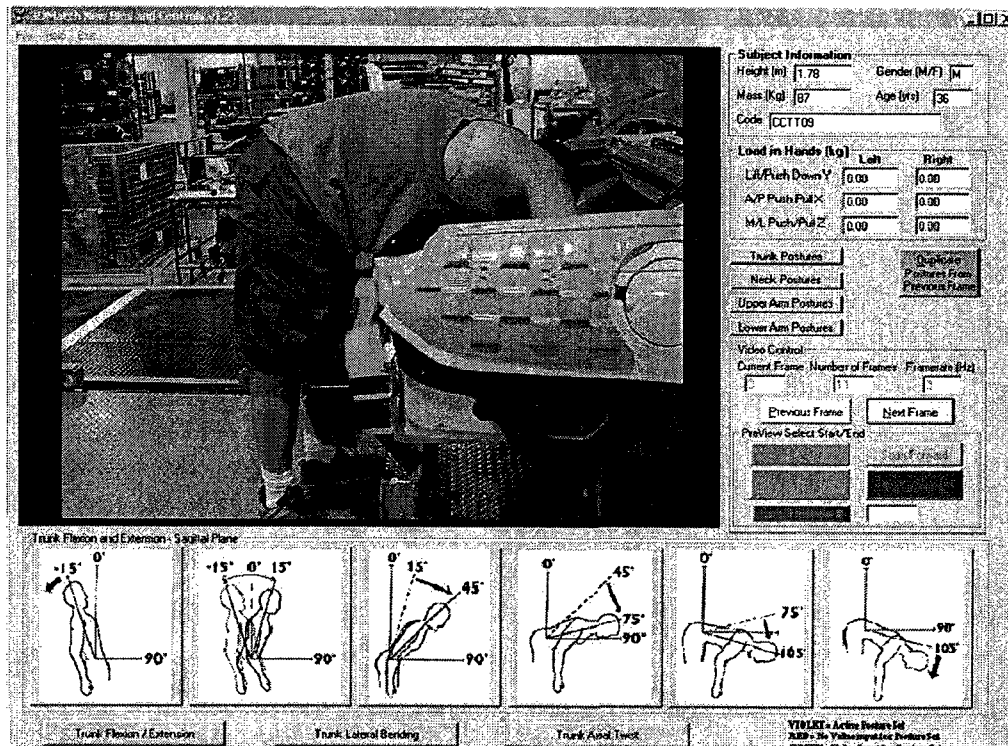


Figure 1. 3DMatch visual interface depicting the trunk flexion/extension posture categories and fields for hand loads and anthropometric inputs.

The accuracy of the calculations of peak and cumulative loads, when using a video-based method such as 3DMatch for postural assessment, has been evaluated (Sutherland et al., 2008; Callaghan et al., 2003). In the preliminary validation of 3DMatch, Callaghan and colleagues (2003) observed that the cumulative load at the lumbar spine was underestimated by about 12%. These observations were performed by comparing the 3D biomechanical model output to the output obtained from a 2D biomechanical model following posture digitization. Sutherland and colleagues (2008) also evaluated the accuracy of low back cumulative loads from 3DMatch by comparing them to the same loads generated by a method using FASTRAK® motion tracking as the posture input method for the biomechanical model. For the study, Sutherland and colleagues (2008) analyzed the difference in using four camera angles. The evaluation showed that the joint compression values obtained by using 3DMatch at any of the four

video recording angles were very consistent with the direct measurements made via motion tracking, having errors below 12% on average. Cann and colleagues (2008) also evaluated the reliability of the values for peak and cumulative loads on the shoulder and lumbar spine when two analysts using 3DMatch performed assessments. The study revealed a reliability of 85.5% on average for all biomechanical output variables.

2.2.2. Posture Classification

The categories used in posture classification interfaces depict sections of the angles involved in the motion range of the evaluated body segment (Lowe, 2004; Callaghan et al., 2003; Keyserling, 1986). The angle range used to define each category for the different views of body segments varies for each categorization system (Lowe, 2004; Callaghan et al., 2003; Hignett & McAtamney, 2000; McAtamney & Corlett, 1993; Keyserling, 1986). Keyserling (1986), for example, used a system which defined trunk posture variations in flexion/extension during standing from <-20 degrees (extension), >-20 to <20 degrees (neutral), >20 to <45 degrees (mild flexion) to >45 degrees (severe flexion), but considered only two categories for trunk lateral bending and rotation (neutral and >20 degrees). He also displayed categories to assess shoulder flexion and abduction of ≤ 45 degrees (neutral), >45 to ≤ 90 degrees (mild) and >90 degrees (severe). 3DMatch (Callaghan et al., 2003) uses a more precise category system for the evaluation of four body segments: trunk, neck, arm and forearm in different views. Trunk and neck are assessed for flexion/extension, lateral bend and axial rotation, using different category sizes. For example, trunk flexion/extension uses 4 categories of 30 degrees ranging from -15 to 105 degrees and 2 categories of undefined size < -15 and >105 degrees (Figure 2); while neck lateral bending uses only 2 categories of 20 degrees, from 0 to 20 degrees and

>20 degrees (Figure 3). For the assessments of shoulder and elbow movements, there are different category sizes ranging from <-20 to >135 degrees for shoulder flexion/extension, <-10 to >135 degrees for shoulder abduction (Figure 4) and 0 to >120 degrees for elbow flexion/extension (Figure 5).

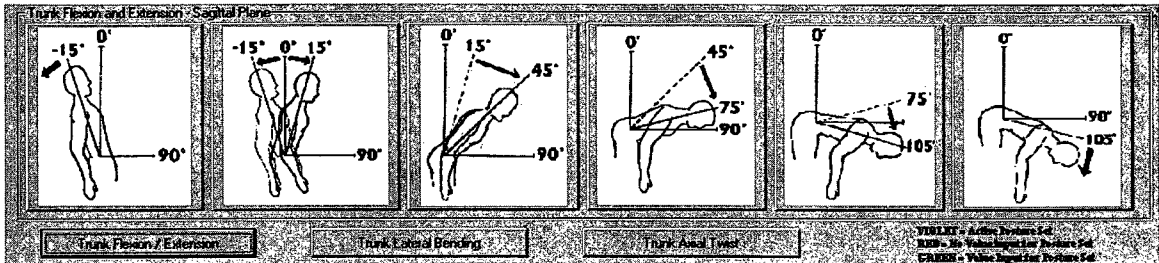


Figure 2. 3DMatch posture categories for trunk flexion/extension assessment.

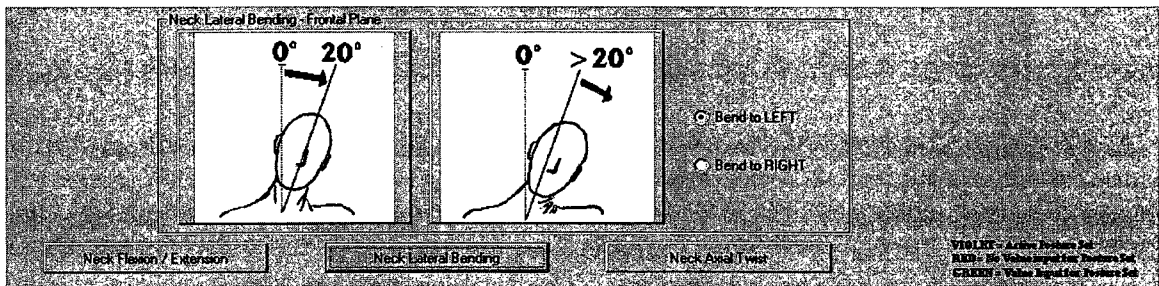


Figure 3. 3DMatch posture categories for neck lateral bend assessment.

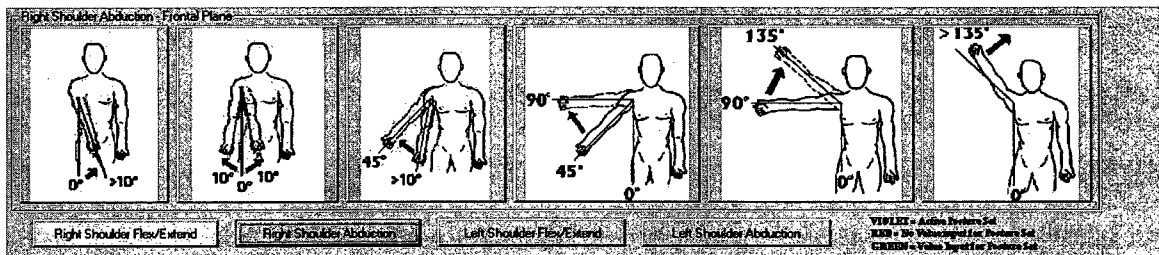


Figure 4. 3DMatch posture categories for right shoulder abduction assessment.

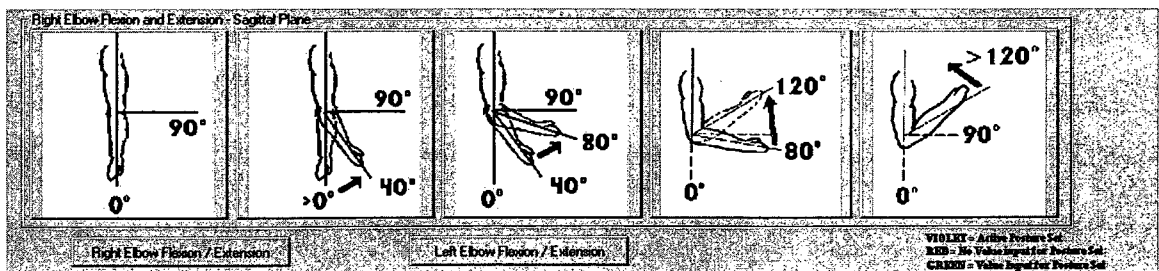


Figure 5. 3DMatch posture categories for right elbow flexion assessment.

As previously mentioned, the accuracy of the outputs generated by a biomechanical model using posture categorization as an input approach, partially depends on the accuracy of classifying body postures (van Wyk et al., 2009; Juul-Kristensen et al., 1997). Similarly, the time needed to complete the classifications has an impact on the efficiency of these biomechanical analysis approaches (Andrews et al., 2008a; Weir et al., 2006; Lowe, 2004). That is why the accuracy of posture classification and the decision time involved in the classification process have been explored in previous research to improve the functionality of video-based assessment methods such as 3DMatch (van Wyk et al., 2009; Andrews et al., 2008a; Andrews et al., 2008b; Weir et al., 2007; Weir et al., 2006).

Analysts performing posture classifications must observe a posture and decide which category best represents the observed posture (Weir et al., 2006); an activity commonly called “posture matching” due to the comparison of a posture to its match or equal within a series of categories. Therefore, the analyst should be able to properly perceive each posture and the available categories to correctly match the posture (Weir et al., 2007). The sensitivity of the visual perception system for posture comparisons was explored by Weir and colleagues (2007), who determined that a user can distinguish between two postures when there is a difference of a minimum of 2 degrees of posture change. This discrimination between postures is called Just Noticeable Difference (JND) and varies in sensitivity depending on the direction of the change. When looking at changes in two trunk postures, a difference of 2 degrees in the flexion/extension or lateral bending angle is sufficient for an analyst to perceive the motion change in an ascending

direction. However, when the change occurs in a descending direction, angles smaller than 7 degrees will be hardly perceived (Weir et al., 2007).

Experience also plays a role in the performance of analysts classifying body postures. Weir and colleagues (2006) observed that experienced analysts can rely on previous knowledge to perform posture classifications more efficiently than novices, who may lack the exposure to such categorization tasks. An average reduction of 0.88 s in the decision time per classification was observed in the performance of novice analysts after classifying 207 postures in a posture matching method similar to 3DMatch. This represents a reduction of 13% of the time required to conduct posture analyses (Andrews et al., 2008b). It has been shown that training benefits novice analysts in reducing the decision time and the number of errors, suggesting an advantage in giving analysts the exposure of practicing posture classifications with an easy training protocol before conducting assessment in real scenarios (Andrews et al., 2008b; Weir et al., 2006).

Nevertheless, all analysts make classification mistakes independent of the experience that they may have using similar posture assessment methods. What is important is to evaluate the impact of the mistakes on the calculation of cumulative and peak loads when making posture classifications, and to determine where the mistakes occur. Andrews and colleagues (2008a) and Lowe (2004) found that most classification errors occur in the category adjacent to the correct one. Andrews and colleagues (2008b) explored the possibility of misclassifying postures when they are close to the category boundaries. They found that between 22% and 32% of the postures that were close to the category boundaries were misclassified compared to postures that were in the middle range of the posture category. The greatest percentage of errors was made in the near

boundary location (16.1%) compared to the midrange (6%) and midline (6.8%) locations. These findings suggest that having less categories will give less category boundaries and therefore, fewer possibilities of postures being presented near the category boundaries (Andrews et al., 2008b, Lowe, 2004; Keyserling, 1986).

Lowe (2004) and van Wyk and colleagues (2009) analyzed the decision time and error rate related to the number of classification categories present in posture matching methods, finding that the decision time increased with the number of categories present. More postures are classified in the correct category when there are fewer and larger posture categories to choose from. However, when a misclassification is made using larger categories, the impact on the biomechanical outputs can be significant (van Wyk et al., 2009; Lowe, 2004). Therefore, posture classification methods require an optimal number of categories, which reflects a tradeoff between the magnitude of the error when a misclassification is made and the number of discriminations needed during the decision taking process (van Wyk et al., 2009). The optimal category size was evaluated by van Wyk and colleagues (2009), who found that the optimal size of the categories on the interface of a video-based assessment method ranged from 15 to 30 degrees. Consequently, there would need to be between three and five categories per view of the body segments involved in a posture. The category sizes used in the current 3DMatch posture diagrams range from 20 to 45 degrees. Andrews and colleagues (2008a) compared the impact that classification errors have on the biomechanical model outputs from 3DMatch, observing that overall, classification mistakes can yield overestimates of the peak and cumulative loads by approximately 13.5% on average. Other studies performed to specifically evaluate the analysts' accuracy in classifying postures using

3DMatch reported an 80.8% agreement between the observers' estimations of posture angles and the measured angles (Sutherland et al., 2007).

All efforts in the previously described studies have been made to improve the decision time and accuracy of video-based posture assessment methods. One aspect that has not yet been evaluated is the perception of the angle range that makes the posture category. The present study will explore some aspects of how the visual recognition of posture categories might be facilitated for analysts using the interfaces of video-based assessment tools.

2.3. Visual Search

2.3.1. Human-Computer Interaction (HCI)

The flow of information between computer users and electronic devices usually occurs via an interface, which defines the communication means between a human and a machine. The information input to the machine is generated by the use of peripheral devices, such as keyboards, light pens, joysticks, touch screens or computer mice (Michalski et al., 2006). The efficiency of the performance in HCI is measured by the speed and accuracy of the interaction, involving the time required for decision time and the amount of errors in the information exchange (Michalski et al., 2006; Bodrogi, 2003; Baylis & Driver, 1995).

Michalski and colleagues (2006) identified the importance of the movements needed to generate any data entry by using peripheral devices, and the visual efforts involved in identifying data entry required for different computer software, in order to perform tasks effectively using computer interfaces. The visual effort consists of visually controlled motor activities and perception (Michalski et al., 2006; Bodrogi, 2003), with

the main purpose of identifying displayed objects in the interface, focusing on finding some objects required to perform specific tasks and discriminating any other objects presented in the visual field (Michalski & Grobelny, 2008; Bodrogi, 2003; Hoffman & Singh, 1997). Many factors can influence visual perception in HCI for identifying key objects such as conciseness, consistency, comprehensibility, legibility, discriminability and detectability (Bodrogi, 2003; International Ergonomic Standard, ISO 9241-12, 1998). This study will focus on the detectability of objects and will refer to it as salience hereafter.

2.3.2. Targets, Distractors and Background

An important function of the visual system is to provide information on the interaction with 3D and 2D objects in order to perform our daily activities (Michalski & Grobelny, 2008). We are permanently guiding our visual attention towards objects of our interest, discriminating the rest of the objects in the environment (Downing, 1988; Treisman & Gormican, 1988), whether it is a physical 3D environment or a 2D display on drawings or on an electronic screen (Michalski & Grobelny, 2008). These actions become visual search tasks, in which we search in our visual field for target objects, among distractors and the background (Figure 6). The object with greater salience is designated by the visual system as the target object and other elements in the scene are perceived as distractors. The space that surrounds the object(s) is perceived as background (Hoffman & Singh, 1997; Wolfe et al., 1992; Treisman & Gormican, 1988).

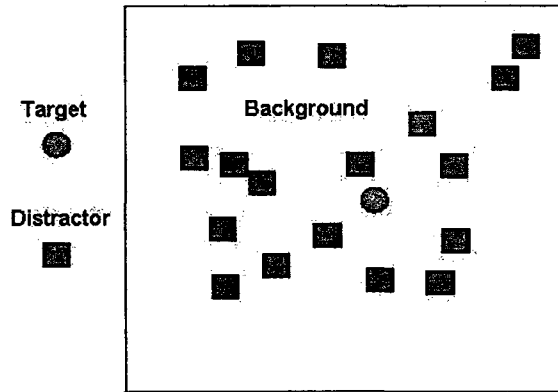


Figure 6. Target object, distractors and background. The target object is the element to which the visual attention is guided, while any other element in the visual field is considered a distractor. The background is the “shapeless” entity that appears to be farthest from the viewer.

In this study, “feature” will be used to define a dimensional value of an object’s characteristic, which provides a stimulus factor to the visual system. These features are the specific magnitude of the characteristic, such as the feature “red” in the characteristic of colour.

2.3.3. Parallel and Serial Processing

Researchers have identified two stages involved in visual information processing, a preattentive or parallel visual perception, and a focused attentive or serial visual perception (Wolfe et al., 1992; Enns & Rensink, 1990; Treisman & Gormican, 1988). Both visual search stages, parallel and serial, have an impact on a person’s efficiency to visually perceive 3D and 2D objects (Michalski & Grobelny, 2008; Nothdurft, 2000; Hoffman & Singh, 1997; Treisman & Gormican, 1988).

The preattentive visual stage occurs when an observer perceives the entire display of his/her visual field at once (Bodrogi, 2003; Treisman & Gormican, 1988), distributing the attention to all objects in a parallel way. This parallel perception characterizes the

objects by the stimulus factors, which originate in the observed objects, such as shape, size, colour, symmetry and convexity. At this stage, target objects are visually separated from other elements in the visual field, like distractors and background. The discrimination is made based on the spatial and structural relationship between the elements, such as pattern, repetitions, salience, orientation, direction of motion, proximity, and temporal position (Nothdurft, 2000; Hoffman & Singh, 1997; Baylis & Driver, 1995; Treisman & Gormican, 1988). At a later stage, focused attentive perception identifies the objects through a cognitive process by serially screening each object in the given space. Serial screening involves memory in order to identify an object by a comparison of its features with familiar ones (Enns & Rensink, 1990; Treisman & Gormican, 1988). During this serial stage, the features of each object are scanned individually and objects with homogeneous features are grouped together, defining also the exact location of entities and groups in the background (Wolfe et al., 1992; Treisman & Gormican, 1988).

Because of its involvement in a cognitive process, serial search requires more processing time than parallel search, which only describes and categorizes the objects' features. As a direct consequence, serial search is less effective in regards to the amount of time required to complete a visual search task (Bodrogi, 2003; Wolfe et al., 1992; Treisman & Gormican, 1988).

The search task at the interface of video-based posture assessment methods such as 3DMatch is focused on the recognition of posture categories (Figures 2, 3, 4 and 5). Posture categories will be the target objects embedded in other elements (distractors) in the diagram, such as the coordinate axes, printed numbers and the human silhouette

(Figure 7), that are not directly related to the matching task. For example, the length of the boundary line or the geometrical elements forming the posture category are not relevant information during the parallel search. This detailed identification of the objects is not needed to perform the posture classification. Therefore, the search task required for the posture categorization should be completed by the detection response of preattentive perception, in order to skip the relatively lengthy serial visual perception (Wolfe et al., 1992; Downing, 1988; Treisman & Gormican, 1988).

Wolfe and Horowitz (2004) refer the identification of each visual search stage to the time used at each one. In their search tasks for different numbers, they reported a time limited by eye movement in the range of 150 to 300 ms, adding 20 to 40 ms per evaluated item during the serial stage; making the parallel stage more time efficient.

The purpose of the current study was to evaluate ways to facilitate the perception of the posture categories as target objects inside the given diagrams at the matching interface, to ensure that the posture movement range is perceived during parallel search rather than during serial search, thereby reducing the analyst's decision time for the task.

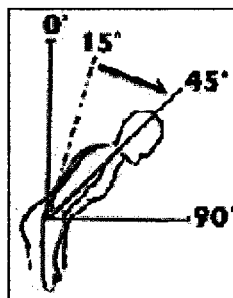


Figure 7. Diagram depicting the posture category of trunk flexion from 15 to 45 degrees. The posture category is the target object and other elements in the diagram will act as distractors.

2.4. Saliency

The visual system during parallel search is sensitive to symmetries and asymmetries between objects, due to similarities or differences in colour, size, geometry, texture or orientation. The asymmetry between objects occurs when a feature of discrete or categorical dimension is present in one of the objects and absent or reduced in the other objects (Treisman & Gormican, 1988). The relative properties between target and distractors, and target and background, are perceived in the preattentive visual stage, without defining the characteristics of each individual object. Consequently, only the object with features not shared with the distractors or with the background becomes salient and will be detected at this preattentive visual stage. Otherwise, this object will be grouped with the other distractors until it is identified by its features during serial processing (Nothdurft, 2000; Downing, 1988; Treisman & Gormican, 1988). Therefore, the capacity of an object to be detected in an early visual search is its saliency, and depends on its relationship with other objects and with the background in the visual field, and not on the object features per se (Nothdurft, 2000).

The magnitude of the asymmetry among objects is perceived differently when the object has more than one distinctive feature (Nothdurft, 2000; Wolfe et al., 1992; Treisman & Gormican, 1988). The saliency produced by the difference between two objects due to a single feature might be modified by the introduction of other features in the relationship, causing an increase or a reduction in the saliency of an object (Nothdurft, 2000). Nothdurft (2000) investigated the effects of a combination of features, finding that although most combinations resulted in additive effects on the saliency, the summation was not linear. The result of adding more features to a target is not necessarily

a proportional increase in salience by the number of added features. For example, a circle among squares will become more salient if the circle is presented in red while the squares are shown in green. Nevertheless, the salience is not doubled, it will only be enhanced. Salience 'reinforcement' by incorporating additional features to a target object is only important when the global asymmetry with the distractors and background in the visual field as a whole, diminishes a salient local asymmetry with the surrounding distractors (Bodrogi, 2003; Nothdurft, 2000; Treisman & Gormican, 1988). The spatial relationship of the elements also causes an effect in the asymmetry. Asymmetry gets attenuated with the increase of distance between the target and the distractor (Downing, 1988). The number of distractors also impacts salience. The larger the group of distractors in the visual field, the lower the effect on the target's salience (Treisman & Gormican, 1988).

There is an increased salience in a target when it possesses a feature that causes the asymmetry among distractors that lack it. When the added feature resides in the distractors, then the salience decreases or is cancelled. For example, a circle having a protuberance is more salient among circles without it than a circle without a protuberance among circles with protuberances (Figure 8). Thus, the relevant asymmetric feature must be present in the target to get the assigned salience (Treisman & Gormican, 1988).

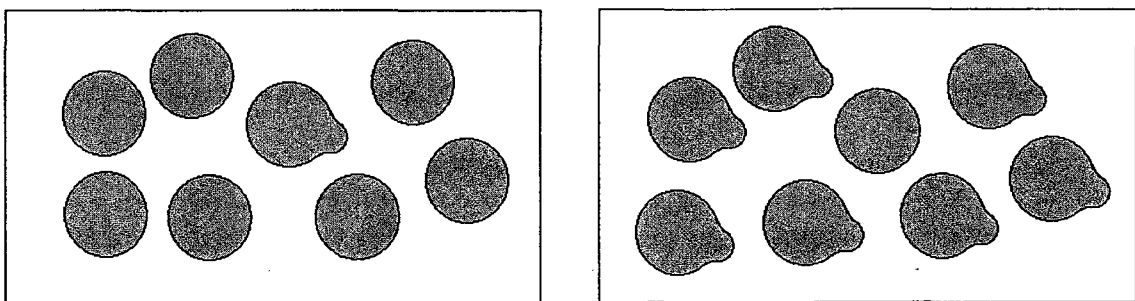


Figure 8. Increased salience of a target object that possesses the feature that causes the asymmetry among distractors that lack it (a). When the added feature resides in the distractors, then the salience decreases or is cancelled (b).

The concept of asymmetry considers salience as a property generated by the relationship of the objects. The relationship among objects determines the level of salience rather than the features of the objects. Therefore, the effectiveness of the visual search depends on the differences in features between the target and the environment with which it interacts (Nothdurft, 2000; Wolfe et al., 1992; Downing, 1988; Treisman & Gormican, 1988).

2.4.1. Salience due to Geometry

In the relationship between objects, the geometrical characteristics of the objects and their boundaries determine their role in the visual field, designating the entity with greater salience as the target object (Nothdurft, 2000; Hoffman & Singh, 1997; Wolfe et al., 1992; Downing, 1988; Treisman & Gormican, 1988). Hoffman and Singh (1997) suggested that the perception of objects starts at defining the objects' boundaries, comparing features to establish relative asymmetries and determining salient entities. However, Baylis & Driver (1995) suggested that the identification of the objects' boundaries is not performed until the target is detected and the salient features are used to define the boundaries. Following either concept, the salience created by the objects' features and boundaries is an important factor for the efficacy of target perception.

The geometrical shape of an object will be considered as one of the object's characteristics and any subset forming the shape will be referred to in this study as the object's part. The projection of the surrounding part of an object's shape into the 2D plane will be referred to as a silhouette. Silhouettes are the most frequent images used in computer visual displays and the focus of this study. Boundaries are the parts of the objects shared either with other objects or with the background. 2D boundaries have

different perceptual representations generated by the differences between the objects that share them, although the boundary belongs to both entities (Hoffman & Singh, 1997; Treisman & Gormican, 1988). The boundary is visually assigned to the more salient object, the target, projecting the other object as a distractor in a deeper visual layer or as a “shapeless” background (Hoffman & Singh, 1997).

Hoffman & Singh (1997) identified several geometrical features that influence the relationship between objects, their boundaries and the salience created by those relations. Those are the size of the parts of an object relative to the whole object, the degree of protrusion of the parts in the object and the visual strength of the boundaries. The area of each part in the object, relative to the size of the whole object’s area, makes the part appear more salient or less salient. This ratio will be constant even if the object is translated, rotated or uniformly scaled. The second geometrical parameter influencing salience, as described by Hoffman & Singh (1997), is the protrusion of a part from its object, which increases the salience of the part as the size of the protrusion increases. Finally, the boundaries of a part can appear as concave and convex curvatures providing different features to the object and to the background. Concave curvatures (crease) are usually perceived to form the object, while the convex component of the same curve is assigned to the background. Thus, the strength of the part boundary depends on what area the crease surrounds; a crease has greater salience than a convex curvature (Hoffman & Singh, 1997).

Treisman and Gormican (1988) and Elder and Zucker (1993) presented the closure of an object (or wholly surrounded area) as a perceptual feature representing the continuity of the silhouette, separable from objects that have open ends. In their

experiments, they observed that a closed circle among circles with gaps could be detected during parallel visual search when the opening of the distractors is large, such as in a semicircle (a gap of 50% aperture). When the gaps were one quarter and one eighth of a circle, the visual search of the closed circle was presumed to occur in the serial stage. This is attributed to the effect of the asymmetry's magnitude between the closed and semi-open circles, when the asymmetry between them increases; the salience of the closed circle also increases. Another explanation for this reduction of asymmetry is that the perception of closure of an object is not affected if the parts in the silhouette are geometrically not completely connected. The visual system may perceive incomplete "closed" silhouettes as closed shapes (Elder & Zucker, 1993). These studies suggest that a closed silhouette is a strong salient feature to guide the attention to an object, facilitating the perception of its shape against the background (Baylis & Driver, 1995; Elder & Zucker, 1993). Thus, the boundary will be perceptually assigned to a closed silhouette rather than a non-closed one; making this closed silhouette, a target object and any feature outside the silhouette will be perceived as background (Baylis & Driver, 1995). Conversely, the boundary will be alternatively assigned to an object or to its background (Figure 9) when there is no salience attributed to any one of them (Hoffman & Singh, 1997, Baylis & Driver, 1995).

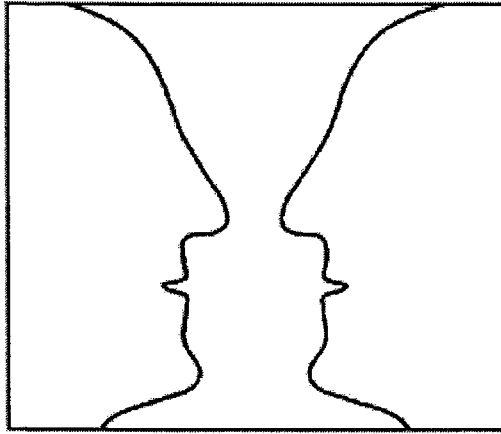


Figure 9. Rubin's classical object-background display (vase-faces) showing how the boundaries can be assigned to an object or to the background when there is no difference in salience (Baylis & Driver, 1995).

The experiments performed by Baylis and Driver (1995) showed that the parallel stage of visual perception dominates in defining object and background during an exposure so short in duration, that no eye movements were involved. Serial search, in comparison, requires more evaluation time because it involves eye movements for the scanning of objects one by one, and involves the memory to identify the objects. This suggests that intentionally applied geometrical features in order to generate salience serve to direct the attention to perceiving an object's shape before it needs to be serially scanned.

The concept of greater salience generated by closed objects is applicable to the visual search task presented in this study, where the posture categories can be presented as a closed object among the open right angles representing the diagram coordinates (Figure 10b). It is hypothesized, that increasing the salience of the posture categories will guide the analyst to perceive it during parallel visual search, discriminating the distractors and the background, and producing a faster response in identifying the category where

the evaluated posture belongs. The visual comparisons that the analysts make of the evaluated posture with the posture categories for each matching task, will take place in the parallel stage of visual perception when no other entities in the display need to be identified in a serial fashion. Additionally, perceiving the posture category in a contained, closed object may help visualize the category size, hypothetically reducing classification errors.

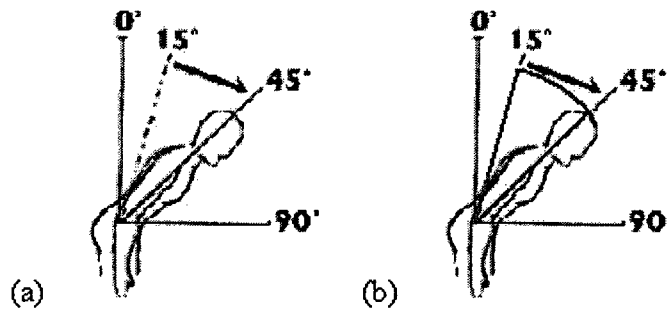


Figure 10. Posture category diagrams depicting trunk flexion from 15 to 45 degrees. The angle range for flexion is presented as an open object (a), and as a closed object to increase its salience (b).

2.4.2. Saliency due to Shading

As explained in the previous section, parallel visual search is involved when defining object boundaries and establishing relationships between objects in the visual field (Hoffman & Singh, 1997). The process of defining objects' boundaries and relationships occurs even in complex natural and artificially displayed visual fields, which may contain overlapping objects (Baylis & Driver, 1995). As human vision tends to interpret 2D displays as 3D scenes by extracting depth cues from features in the objects (Sun & Perona, 1996; Baylis & Driver, 1995; Enns & Rensink, 1990), the boundaries of overlapping objects cannot be assigned to two objects at the same time. Therefore, the definition of object and background must occur by assigning depth layers at the scene and placing the object in one layer and the background in another, when confronted with overlapping objects in a 2D display (Enns & Rensink, 1990). The boundaries will then be perceived as belonging to one object at one scene layer, depending on the features of the boundary, and appearing as the closer entity to the observer, while the other object or the background will visually remain behind it (da Pos et al., 2007; Enns & Rensink, 1990).

The boundaries of two overlapping opaque objects, achromatic or coloured, are assigned to the object that has more salient geometrical features such as closure, internal concave areas, or boundaries that appear larger in relation to the whole object (Hoffman & Singh, 1997; Baylis & Driver, 1995). However, there may also be overlapping objects in the visual field in which the boundary may not only be a border but an area. This area shows transparency, making one object visually appear in front of the other and the boundaries of the one below will still be perceived (da Pos et al., 2007). This

transparency will be referred to in this study as shading. The term “achromatic” will be used to describe any entity with a colouration contained in the range from white to black.

Masin (2000) analyzed the relationships of shared areas between objects, which generate shading, finding that in achromatic overlapping objects the visual system relates the difference in the grey scale of each object with the overlapped area. This results in the assigning of the shading to the object more similar to this area, visually locating it to a front layer and making it salient. When there is no shading generated at overlapping objects (Figure 11a), the objects appear in the same visual layer and no salience is attributed to any object to become the target object. Similarly, when shading is equally assigned to either object (Figure 11b) both objects alternate to be in front of the other (Masin, 2000). Moreover, a lower contrast between the shared area and one of the objects will assign the shading to that object (Figure 11c), making the other one opaque and locating it in a layer below (da Pos et al., 2007; Masin, 2000).

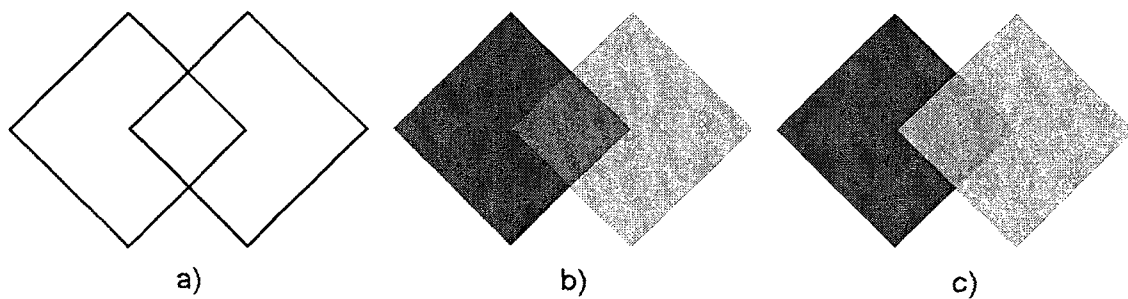


Figure 11. No shading generated at two overlapping silhouettes (a), or equally assigned to two objects (b) generates no salience in any of the objects, whereas the shading assigned to the object at the right in (c) makes it the target object at the front and therefore more salient (Masin, 2000).

It is believed in the present study, that generating shading in the posture category will increase the salience of this area by visually positioning it as a front layer and making it the target object in the visual search (Figure 12). If this is the case, for posture assessment methods, the shading of the posture category will guide the attention of the visual system to perceive the range during the parallel stage of the search, and therefore result in faster detection.

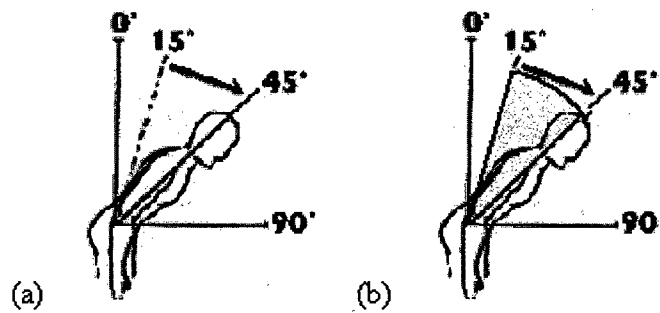


Figure 12. Posture category diagrams depicting trunk flexion from 15 to 45 degrees. The shaded angle range for flexion (b) increases the salience of the posture range by presenting it nearer to the observer, while in the non-shaded angle range for flexion (a), all elements appear at the same visual layer.

2.4.3. Saliency due to Colour

Colour can produce asymmetries when a target object and distractors differ on a single perceptual component of colour, such as hue, saturation or brightness (Bodrogi, 2003; Treisman & Gormican, 1988). Four basic hues are commonly used in displays to create differences in objects: red, blue, yellow and green, defined through the opponent colour systems, such as CIELAB (Commission Internationale d'Eclairage/International Commission on Illumination with the components of Lightness and A and B colour axes). According to these systems, stimuli are translated into distinctions between red and green, and blue and yellow, based on the fact that a colour can't be both red and green, or blue and yellow because these colours oppose each other (D'Zmura, 1991; Nagy & Sanchez, 1990). The perceptual asymmetry of colours belonging to different hues is stronger than the distinction of those within a hue, although the latter may present a larger difference in their wavelengths (Brodogi, 2003). Therefore, it is more effective to use any of the basic hues to generate asymmetries between objects in a display rather than colours containing combinations of hues (D'Zmura, 1991).

Bodrogi (2003) proposed a method to measure the saliency of a coloured target among other coloured and grey distractors as the inverse of the search time. He proposed that in displays with many entities, the relationship between the target object and each distractor produced a saliency level and used the search time length to determine the hierarchy of that level. Greater levels of saliency led to shorter search time.

This concept of levels of saliency is applicable to the design of displays that have several target objects and require the prioritization of the detection of each target (Bodrogi, 2003). Colour is suggested as a guiding characteristic to detect an object during

the parallel stage of the visual search. This was observed in experiments involving search tasks where the target object was different to the distractors only by colour (D’Zmura, 1991). D’Zmura (1991) explains the search by colour in a parallel stage, as the result of visual mechanisms acting as filters. An example from his study shows that the search of an orange target in the presence of three sets of distractors: blue and red in one scenario, yellow and blue, and yellow-green and purple in two other scenarios, did not differ in regards to the search time. However, the search time for an orange target in the presence of yellow and red distractors increased substantially. The difference in search time can be explained by the visual mechanism used to search for colour in that people can only filter one shared value (yellow or red) between the target and the distractors during a parallel search. Therefore, when two features, shared between target and distractors, are simultaneously present in the visual field, then a simple filter mechanism cannot be used and the objects must be serially sought (D’Zmura, 1991). In the case that two features (yellow and red) of the same characteristic (colour) are shared between target and distractors, comparable target-distractor differences are created, generating no salience in the relationships. Only the asymmetries created by the difference of a single perceptual component of colour will be perceived at the parallel visual stage (Nagy & Sanchez, 1990; Treisman & Gormican, 1988).

Nagy and Sanchez (1990) explored the correlation between the size of the colour difference and the search time, finding that the search time decreases linearly with increasing colour difference, but reaches a difference magnitude where search time remains constant even if the colour difference keeps on increasing (Nagy & Sanchez, 1990). Although asymmetry is found between a target and distractors when they differ on

a single perceptual component of colour if the colour difference is small, there will not be salience in that relationship and therefore the identification of the target and distractors will occur during serial visual search (Nagy & Sanchez, 1990; Treisman & Gormican, 1988). The colour difference is also logically achieved by the presence of colour among achromatic objects. The presence of a perceptual colour component, hue, produces the asymmetry between the colour and non-colour objects, which is perceived in the parallel stage of visual search.

Michalski and Grobelny (2008) reported a considerable effect of colour in the search time for letters and numbers on a computer display. They measured the search time for letters presented in individual colour squares on a screen, finding a 15% average reduction in search time for letters or numbers on coloured target squares compared to a similar search using grey squares. However, the error rates in selecting a requested letter or number in the same study did not show a difference when the letters and numbers were presented in colour or grey backgrounds.

The behavior of assigned transparency, when dealing with overlapping achromatic objects, is also observed in objects with colours. The object presenting the lowest hue asymmetry with the shared area is assigned the shading and perceived in the foreground, while the one presenting greater hue asymmetry with the shared area is visually positioned in the background (da Pos et al., 2007). da Pos and colleagues (2007) observed that asymmetry can be generated with variations only in hue without modifying the luminance.

The importance in this study for understanding the salience that colour produces in the visual perception of objects, resides in its application to the design of displays in

which visual search for objects is required to perform an input during HCI. The introduction of an adequate colour difference between displayed objects, target and distractors, will result in a shorter search time for target objects, and therefore a more efficient use of the interface. Video-based posture assessment methods which use computer interfaces for posture categorization, such as 3DMatch (Callaghan et al., 2003), may benefit from the use of colour in their visual displays.

The use of salience for visual search tasks has the purpose to facilitate the perception of objects in the parallel search rather than being identified serially, if efficiency is to be achieved. There are several conditions that exclude the lengthy serial stage of the visual search during HCI task. In order to achieve this, the target object must be salient, using one or a number of specific characteristics. Additionally, the salience generated by different conditions to perceive the posture category as the target object will highlight the category size, facilitating the matching process and possibly reducing classification errors. The purpose of this study was to determine which of these characteristics will facilitate visual search and to determine the degree of each of their contributions.

Chapter III

METHODOLOGY

3.1. Participants

Ninety students (45 males and 45 females), enrolled at the University of Windsor in undergraduate and graduate programs, were recruited to participate in this study (Table 1). The recruitment was performed by e-mail announcements to each department of the University and by a publication on the University's Daily News. The participants had various educational backgrounds and belonged to a range of programs including Human Kinetics, Psychology, Engineering, Biology, Mathematics, Arts & Social Science, Political Science and Nursing (Table 2). To be included in the study, participants were not to have had experience in video-based posture assessment methods and had to have normal or corrected to normal visual acuity. The students provided written informed consent for their participation in the study, in accordance with the approval by the Research Ethics Board of the University of Windsor (Appendix C).

Table 1. Mean (SD) Participant Information

	Female (n=45)	Male (n=45)
Age (yrs)	21.8 (4.4)	22.2 (3.5)
Height (m)	1.68 (0.07)	1.80 (0.09)
Mass (kg)	62.9 (9.7)	79.4(12.9)

Table 2. Number of Participants per Faculty

Faculty \ Gender	Arts & Social Sciences	Engineering	Human Kinetics	Nursing	Science
Female	6	0	37	0	2
Male	3	9	28	1	4

3.2. Experimental Environment

The experiment was conducted at the University of Windsor in the Computer Lab located on the second floor of the Faculty of Human Kinetics building. This lab consists of a room with 58 computers distributed in two sections. One section is arranged with 40 computers set in four parallel rows. The other section has 18 computers arranged in a square fashion. The smaller section was used for the study and was separated from the larger section by a sliding wall that provided a visual and noise barrier. The room had standard, artificial and natural illumination required for this type of lab, with T8 high efficiency fluorescent lamps and 2 windows located at the rear wall. The experiment took place in similar conditions compared to standard office work environments.

3.3. Apparatus

The experimental apparatus for each participant consisted of one of the computers in the lab, including its monitor and mouse, and experimental software for posture classification. The interface provided by the software, similar to the 3DMatch interface (Figure 1), showed still images of a man in known flexion/extension postures of the trunk, shoulder and elbow in the upper part of the computer screen, and posture categories in the lower part (Figure 13). The interface functioned by displaying posture images to the participant and receiving the input of a selected posture category from the participant via the computer mouse. The software recorded the time between the display of the image and the mouse click and the number assigned to the selected category. Once a posture was selected, a new cycle started with the display of another image and another set of posture categories.

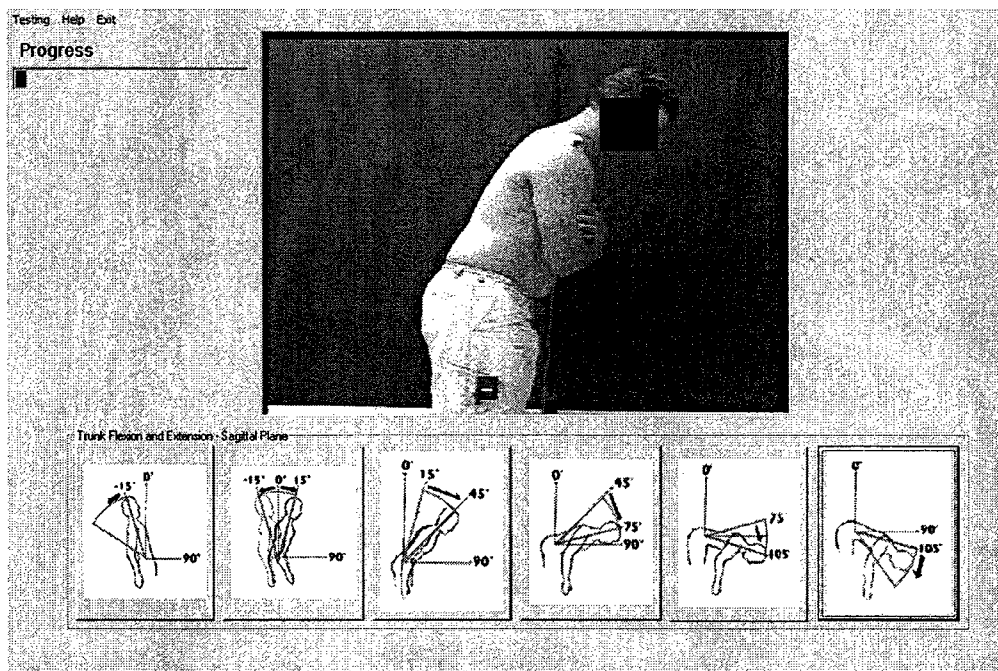


Figure 13. Experimental interface depicting the trunk flexion/extension variable with grey border (GB) posture categories.

3.3.1. Salience Conditions Displayed in the Experimental Interface

This study intended to examine the concepts of salience applied to the visual interface of posture assessment methods. Four variations to the posture category diagrams (Plain) from 3DMatch (Callaghan et al., 2003) were included for evaluation: The presentation of the posture category as a closed object using achromatic (grey) boundaries (GB) to increase its salience among other objects in the diagram (Figure 14); the addition of red colour to the boundaries (RB) of the closed posture category (Figure 15); the addition of achromatic (grey) shading (GS) to the posture categories to increase their salience by visually placing it nearer to the observer (Figure 16); and the addition of colour to the posture category shading (RS) (Figure 17). The colour included was red, as it is one of the four basic perceptual hues used in colour description systems like CIELAB (Nagy & Sanchez, 1990).

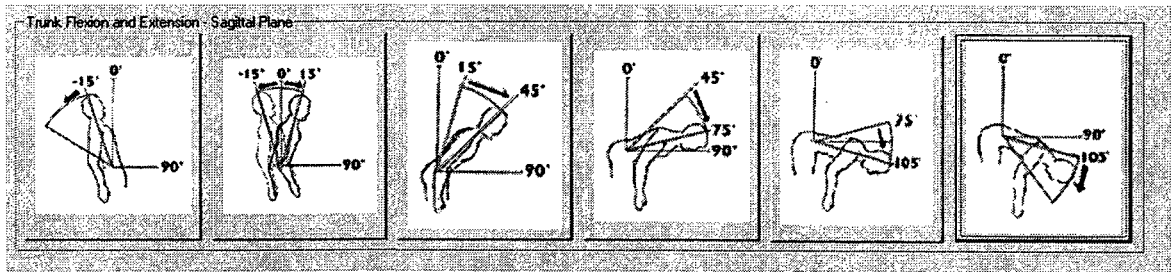


Figure 14. Posture categories displaying achromatic border (grey) for added salience (GB).

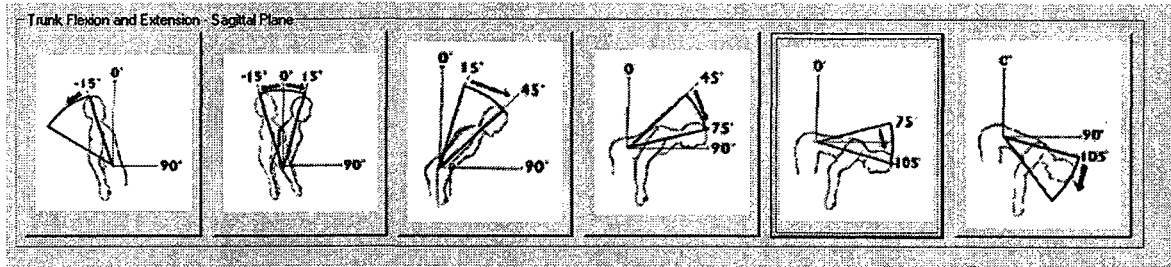


Figure 15. Posture categories displaying a colour border (red) for added salience (RB).

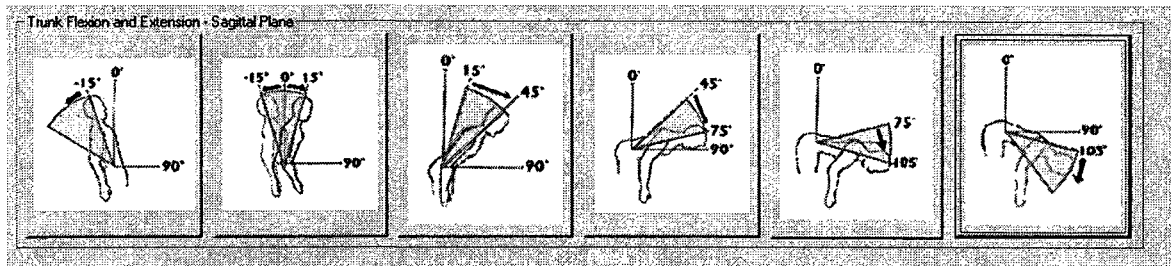


Figure 16. Posture categories displaying achromatic shading (grey) for added salience (GS).

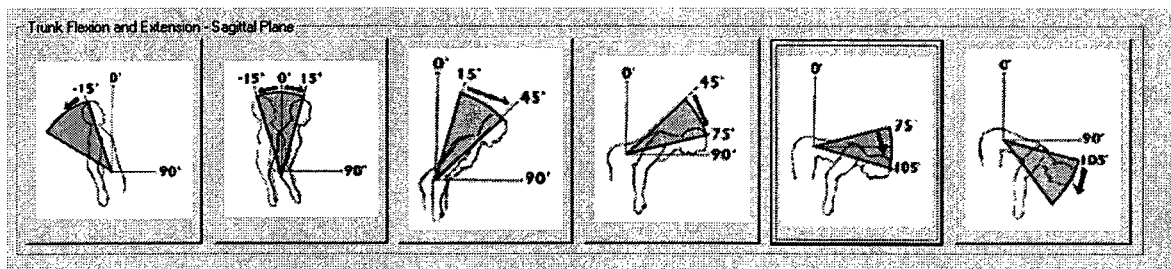


Figure 17. Posture categories displaying colour shading (red) for added salience (RS).

3.4. Methods

3.4.1. Procedures

The participants' age and anthropometric measures (height and body mass) were recorded in the Biomechanics Lab, where they were also assigned a testing code that put them in one of the six counterbalanced testing sequences (described below). Fifteen participants were assigned to each of the six presentation sequences. The student researcher and participant(s) then walked to the Computer Lab to start the testing session.

The participants were instructed to sit at one of the computers in the lab, the interface of which was set to the appropriate presentation sequence by the researcher. Before receiving their first image, participants were instructed as follows:

1. Observe the images of a person in different postures at the top of the computer screen like those in the diagrams [examples of postures of trunk, shoulder and elbow flexion were shown to the participants on a paper diagram (Appendix A)].
2. Click with the computer mouse on the posture category at the bottom of the screen, the diagram that you think best represents the posture of the person in the image at the top of the screen.
3. Once you select one diagram, a new posture image will show up. This will repeat throughout the complete test.
4. Do the selection as fast and as accurately as possible throughout the complete set of images.
5. Once you have completed the whole test, the program will indicate so and will ask you to exit. Click OK.
6. After you are finished on the computer, fill out the short questionnaire.

Once the participants categorized the postures that were presented, the program finished. Participants then filled out a questionnaire asking them about their perception of what conditions were the easiest, most difficult, and fastest and which ones resulted in fewest errors. They were also asked to describe the strategy they used when selecting the posture diagrams (Appendix B).

During testing, flexion and extension images with known angles for three body segments (trunk, shoulder and elbow) were presented. There was one image representing a posture for five of the six categories of trunk flexion and extension (Figure 2), six categories of right shoulder flexion and extension, and five categories of right elbow flexion (Figure 5). The missing posture for the evaluation of the trunk was trunk extension. In most cases, the presented images depicted postures located in the middle of the posture category, in order to control for the effect that proximity to the category boundaries has on misclassification errors (Andrews et al., 2008b). However, due to the availability of images, several images were presented that had known angles not directly in the middle of the categories, these included: 120 degrees of trunk flexion was replaced by 115 degrees of trunk flexion; 32.5 degrees of shoulder extension was replaced by 32 degrees; 0, 32.5, 67.5, 112.5 and 157.5 degrees of shoulder flexion were replaced by 1, 32, 67, 112 and 157 degrees, respectively; and 0, 20 and 140 degrees of elbow flexion were replaced by 15, 35 and 139 degrees, respectively. The largest deviation was 15 degrees for elbow flexion for two posture categories (i.e. 0 and between 0 to 40 degrees), with most substituted images being within a few degrees of the middle of the categories.

The posture images were randomly presented 3 times for each of the five salience conditions (i.e. current 3DMatch display, grey border, red border, grey shading, and red

shading), within a block of postures of the same body segment. Each participant observed the same blocks of images, but presented in a different order. There were six possible block presentation sequences: trunk-shoulder-elbow, trunk-elbow-shoulder, shoulder-elbow-trunk, shoulder-trunk-elbow, elbow-trunk-shoulder, and elbow-shoulder-trunk. Each participant performed a total of 240 trials consisting of the classification of one posture. Each image was presented 3 times for each of the 5 posture categories for the trunk and elbow, and for each of the 6 categories for the shoulder in all 5 salience conditions (i.e. (5 trunk postures x 3 repetitions x 5 salience conditions) + (6 shoulder postures x 3 repetitions x 5 salience conditions) + (5 elbow postures x 3 repetitions x 5 salience conditions) = 240 trials). The total time to complete the testing session was approximately 30 minutes.

The data collected during each trial included decision time (seconds), whether a classification error was made, and the relative position of the error with respect to the correct category. Decision time was defined as the period between the display of the image and the selection of the posture category using the mouse. An error was recorded when an incorrect category was selected. The relative position of an error was recorded as a number from -5 to -1 and 1 to 5, with each number representing a category to the left (-) or right (+) of the correct category (0), respectively.

3.4.2. Experimental Design

The data were modeled in a 5 x 3 x 3 x 2 (Salience Condition x Body Segment x Repetition x Gender) mixed design. The within subject factors (repeated measures) were the Salience Condition (Plain, GB, RB, GS, RS), Body Segment (Trunk, Shoulder,

Elbow), and Repetition (1st, 2nd, 3rd). Gender (female, male) was the between subject factor (Table 2).

There were two dependent variables, decision time and error rate. The decision time was obtained directly from the participants' response recorded at every trial and error rate represented the number of classification errors made as a percentage of the number of trials performed at each combination of Saliency Condition, Body Segment and Repetition. Additionally, the magnitude of the error was obtained from the location of the classification error relative to the correct posture category for further evaluation.

Table 3. Mixed Experimental Design

Saliency	Current Display (Plain)						Grey Border (GB)						Red Border (RB)						Grey Shading (GS)						Red Shading (RS)											
Body Segment	Trunk		Shoulder		Elbow		Trunk		Shoulder		Elbow		Trunk		Shoulder		Elbow		Trunk		Shoulder		Elbow		Trunk		Shoulder		Elbow							
Repetition	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3			
Gender																																				
Male																																				
Female																																				

Dependent Variables: Decision Time and Error Rate

3.4.3. Data Processing

The software recorded decision time, errors and error location for each trial in a format transferable to a Microsoft Excel ® spreadsheet. The data were organized in Excel 2007 and outliers were treated. Outliers were defined as values exceeding 2 Standard Deviations relative to the mean. Statistical analyses were performed with PASW (Predictive Analytics Software) Statistics 18.0 (SPSS Inc., an IBM Company).

3.4.4. Statistical Analysis

The dependent variables, decision time and error rate, were analyzed using a 4 way (5 Saliency Conditions X 3 Body Segments X 3 Repetitions X 2 Gender) analysis of variance (ANOVA) with repeated measures on Saliency Condition, Body Segment and Repetitions. For significant main effects and interactions, post hoc testing was performed using Tukey's Honestly Significant Difference (HSD), with critical significance level (α) set at $p \leq 0.05$. An omega squared (ω^2) estimate of variance was calculated for all significant interactions. Interactions accounting for less than 1% of the total variance were excluded from further analysis (Keppel, 1982).

The data for the analyses of decision time and error rates violated the assumption of sphericity, for which Greenhouse-Geisser adjustments were performed (Vincent, 2005).

The Lvene's statistic for both decision time and error rates were not significant at $p < 0.05$. Therefore, it was assumed that the variance among the repeated measures of each dependent variable was homogeneous.

Chapter IV

RESULTS

4.1. Effect of Salience Condition on Decision Time and Error Rate

There were significant main effects of Salience Condition (Plain, GB, RB, GS, RS) on decision time [$F(3.0, 261.8) = 58.33, p < 0.05$] (Appendix D) and error rate [$F(3.6, 314.1) = 18.67, p < 0.05$] (Appendix E). For decision time, all salience conditions were significantly different from one another, except Plain and RS (Figure 18). For error rate, the salience conditions were also significantly different from one another, except Plain and GS, GB and RB, GB and RS and RB and RS (Figure 19).

The fastest responses among the participants were found in the two border conditions, GB and RB, with mean decision times (SE) of 2.10 s (0.10) and 2.14 s (0.09), respectively. The slowest mean decision times were for RS and Plain conditions with the RS condition being on average 0.14 s and the Plain condition 0.12 s longer than the fastest condition (GB) (Figure 18).

There was a reduction in error rates relative to the Plain condition when the participants were exposed to diagrams showing red and grey borders and red shading in the posture categories (Figure 19). The reduction of error rates ranged from 1% to 1.5%, having GB the smallest reduction and RB and RS the largest reduction.

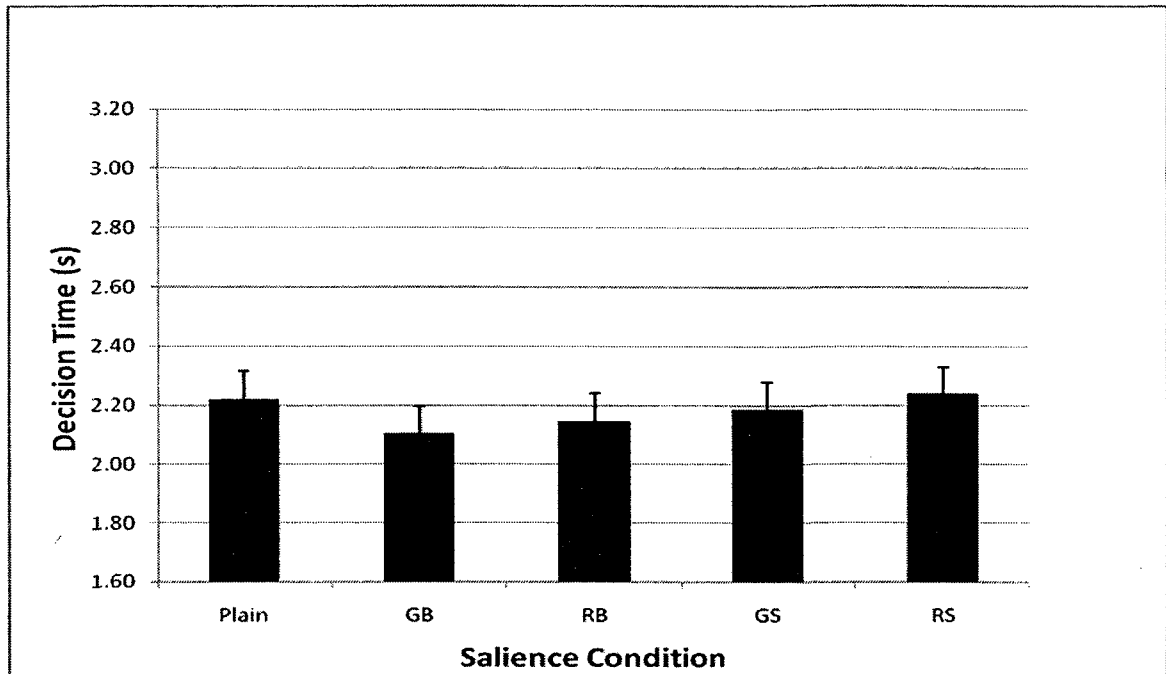


Figure 18. Decision time as a function of Salience Condition [Plain, Grey Border (GB), Red Border (RB), Grey Shading (GS), and Red Shading (RS)]. All conditions were significantly different from one another ($p < 0.05$), except Plain and RS.

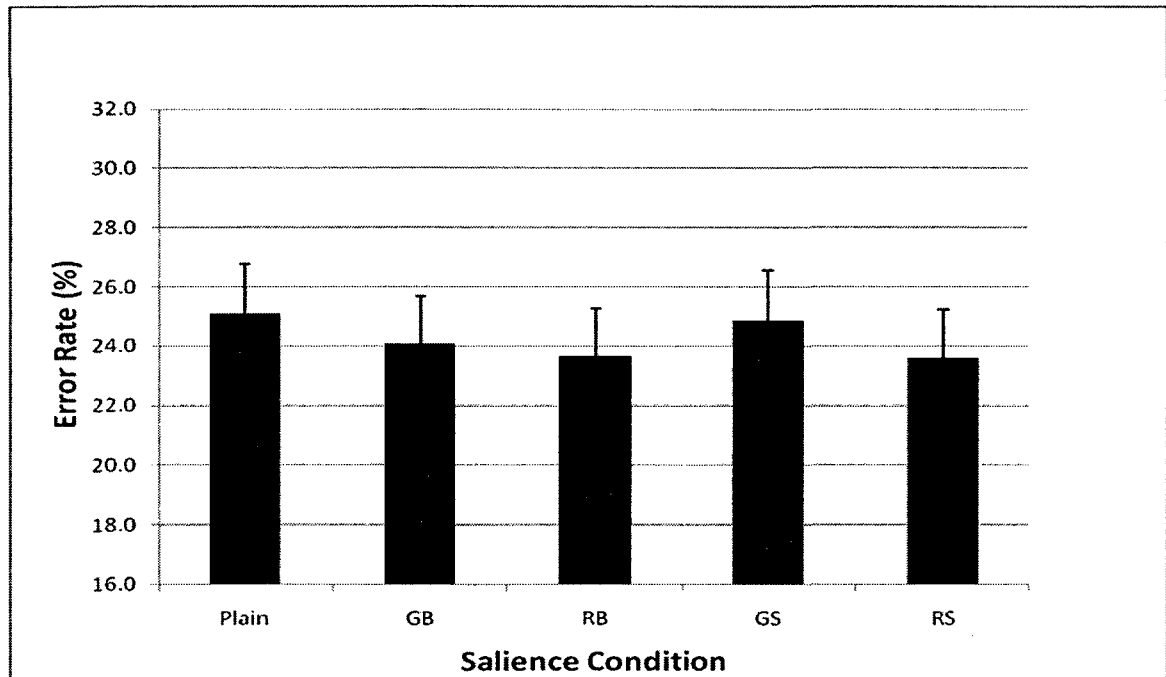


Figure 19. Error rate as a function of Salience Condition [Plain, Grey Border (GB), Red Border (RB), Grey Shading (GS), and Red Shading (RS)]. All conditions were significantly different from one another ($p < 0.05$), except Plain and GS, GB and RB, GB and RS and RB and RS.

4.2. Effect of Body Segment on Decision Time and Error Rate

Significant main effects of Body Segment (Trunk, Shoulder, Elbow) were also found for decision time [$F(1.8, 154.4) = 119.9, p < 0.05$] (Appendix D) and for error rate [$F(1.4, 127.0) = 95.9, p < 0.05$] (Appendix E). The participants classified elbow postures on average 0.16 s faster than trunk postures and 0.21 s faster than shoulder postures. Assessing trunk postures was 0.05 s faster than assessing shoulder postures (Figure 20).

Participants classifying shoulder postures made on average 8.9% fewer errors than classifying trunk postures and 9.3% fewer errors than classifying elbow postures. The difference in error rates between classifying trunk and elbow postures was not significant (Figure 21).

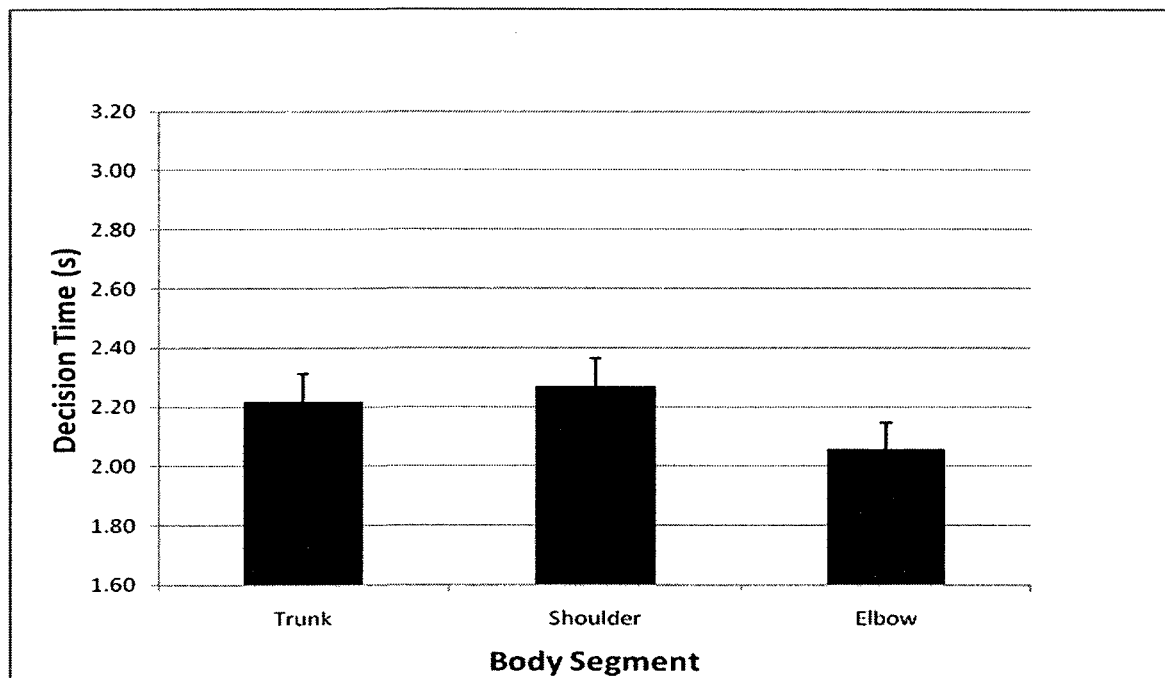


Figure 20. Decision time as a function of Body Segment. All levels of Body Segment were significantly different from one another ($p < 0.05$).

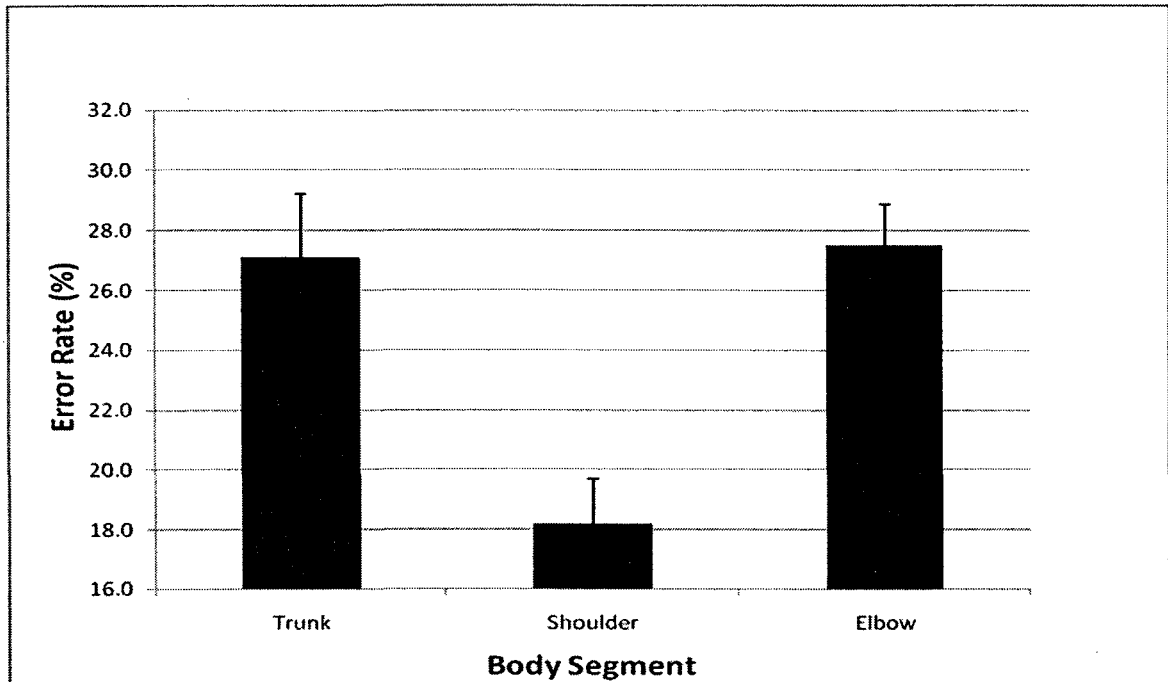


Figure 21. Error rate as a function of Body Segment. All levels of Body Segment were significantly different from one another ($p < 0.05$), except for Trunk and Elbow.

4.3. Effect of Repetition on Decision Time and Error Rate

There was a significant main effect of Repetition on both the participants' decision time [$F(1.0, 88.6) = 211.8, p < 0.05$] (Appendix D), and error rate [$F(1.5, 139.4) = 69.14, p < 0.05$] (Appendix E). All levels of Repetition were significantly different from one another for decision time (Figure 22) and error rate (Figure 23).

These main effects were involved in a significant interaction, and therefore will be further described in Section 4.4.

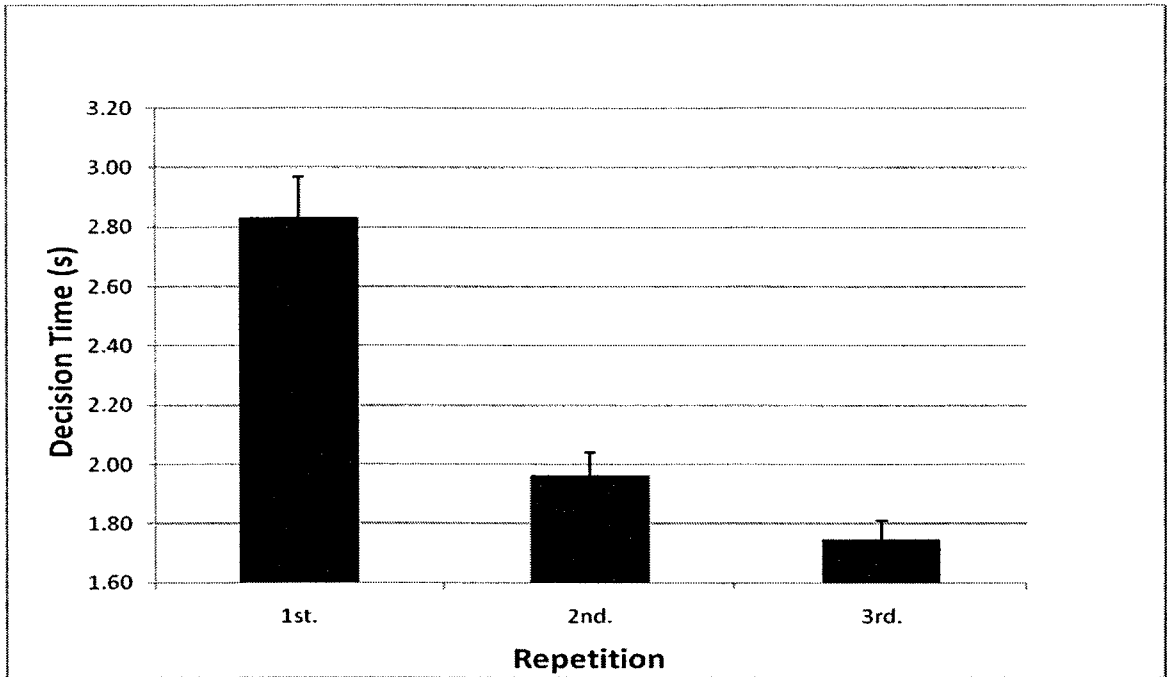


Figure 22. Decision time as a function of Repetition. All levels of Repetition were significantly different from one another ($p < 0.05$).

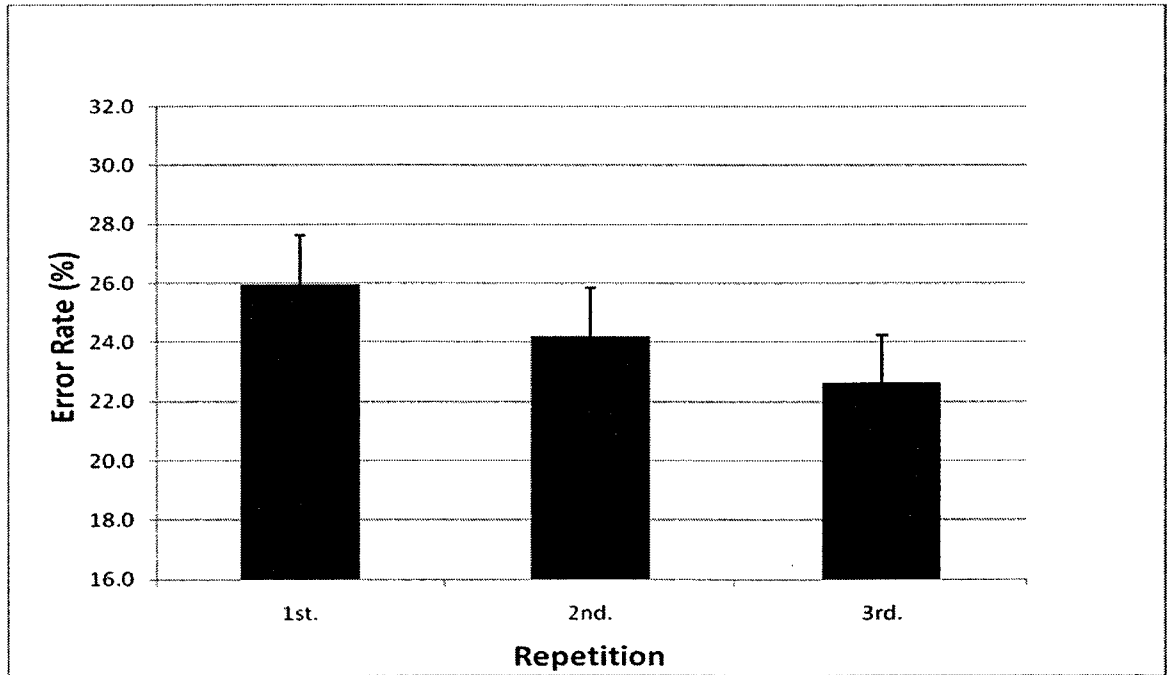


Figure 23. Error rate as a function of Repetition. All levels of Repetition were significantly different from one another ($p < 0.05$).

4.4. Repetition x Gender Interaction

There was a significant interaction between Repetition and Gender for decision time [$F(1, 88.6) = 6.7, p \leq 0.05, (\omega^2 = 0.015)$]. Female participants were significantly faster than male participants on Repetition 1 only, showing a speed advantage of 15.6%. The decision times for males and females were not significantly different on Repetition 2 and 3 (Figure 24).

Female and male participants had an overall reduction in decision time of 30.4% on average between the first and the second exposures to the same images. There was also a reduction in classification speed of 11% on average between Repetition 2 and Repetition 3.

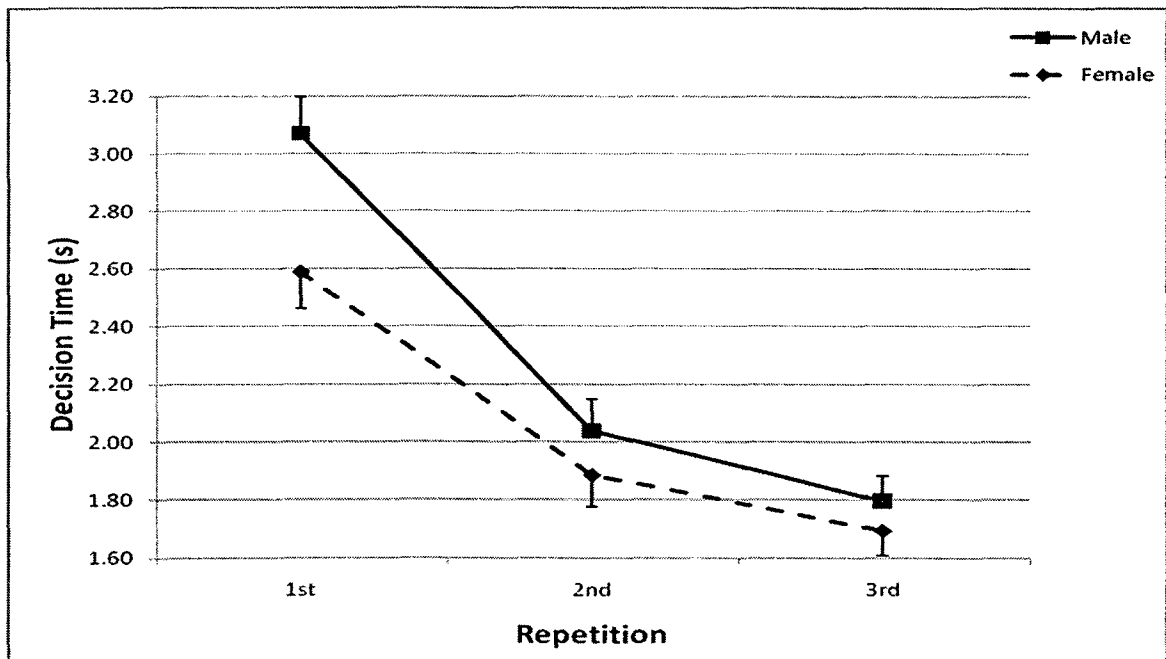


Figure 24. Repetition x Gender interaction for decision time. Female and Male groups were significantly different at the 1st repetition but not significantly different at the 2nd and 3rd repetitions ($p < 0.05$).

The Repetition by Gender interaction for error rate was not significant (Figure 25). Females and males reduced their error rates equally when they classified postures for the second and third times. The mean reduction in error rates between the first and second, and second and third exposures to the same image were 1.7% and 1.6%, respectively.

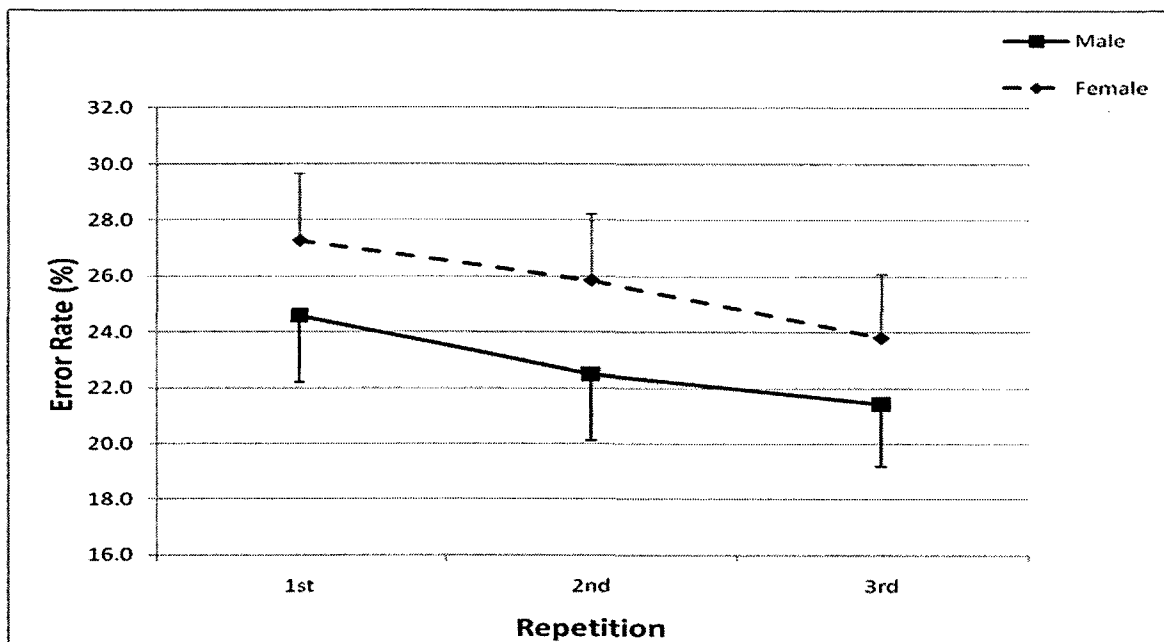


Figure 25. Repetition x Gender interaction for error rate. This interaction was not significant, as male and female participants performed similarly at each repetition.

4.5. Participants' Perception of Salience

The written questionnaires filled in by the participants showed that 54.4% of the analysts judged the current Plain display as the most difficult for posture matching, followed by RS (16.7% of the participants).

The posture categories with added colour, RB and RS, were perceived as the easiest for the posture matching by 35.6% and 36.7% of the participants, respectively.

Similarly, 33.3% and 32.2% perceived the RB and RS conditions to be those that resulted in the fastest responses (Figure 26).

In regards to the perception of error rates, the participants perceived that the RB (35.6%) and RS (34.1%) conditions would yield less classification errors overall (Figure 26).

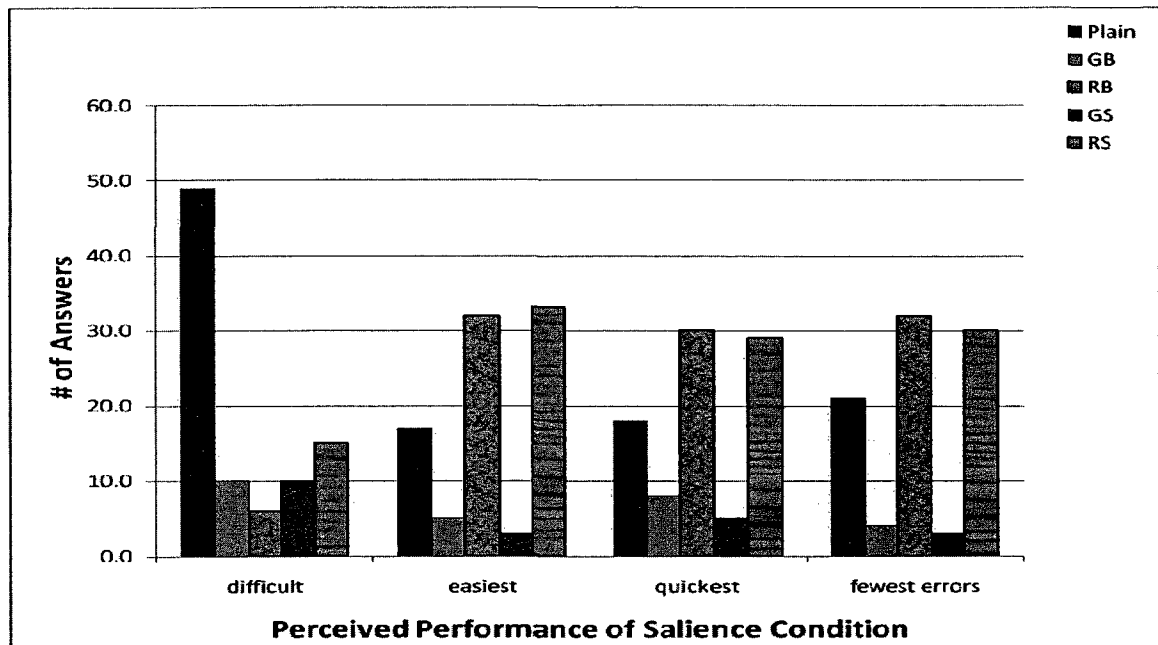


Figure 26. Participants' perception of Salience Condition. The participants' perceived performance quantified by the number of answers.

4.5.1. Participants' Perceived Strategies

The participants' written questionnaires included a section to indicate the strategy that they followed to complete the task. Overall, the two strategies that were used the most were to visualize the person's posture in the image (27.8%) and to use the axes in the diagrams to help guide the position of the segment (23.3%) (Table 4). Some participants indicated that they used strategies supported by the posture category salience. Over 15% of the participants used the category boundaries to evaluate if the depicted

posture image fit in the category and 11.1% used the shaded areas to perform the same evaluation. About one-sixth of the participants indicated that they felt they became faster in the task and found it easier to classify postures the more repetitions they experienced.

Table 4. Strategies Used by the Participants

Strategy	# of Answers	% of Participants reported
Comparison to 0° and 90° axis (also to 45° angle)	21	23.3%
Visualizing /Calculating depicted person's posture angle	25	27.8%
Created motion image	10	11.1%
Glance/Comparison between pictures and diagrams	16	17.8%
Superimpose pictures and diagrams	3	3.3%
Memorized diagram positions	13	14.4%
Compared to boundaries to fit the depicted posture angle	14	15.6%
Compared to shaded areas to fit the depicted posture angle	10	11.1%
Ignored salient border	7	7.8%
Ignored salient shading	9	10.0%
Simply guessing	2	2.2%
No strategy/No answer	4	4.4%
Mentioned repetition for the task becoming quicker and easier	12	13.3%
Got distracted / confused with the borders	3	3.3%
Got distracted / confused with the shadings	6	6.7%

4.6. Magnitude and Location of the Classification Errors

Approximately 99% of the classifications made in this study occurred either in the correct category or within one category to the right or left of the correct category (Figure 27) (Note: Since no classification errors were made at the extremes of the distributions, i.e. in the -5, -4, 4 and 5 categories relative to the correct category (0), these categories were excluded from the graphical presentations in Figures 27 to 31). Over 73% of the classifications were made in the correct posture category, and of the total of classification errors (26.5%), 15.6% were overestimations (classifications made in the posture categories at the right of the correct one) and 10.9% were underestimations (classifications made in the posture categories at the left of the correct one). The highest

concentration of overestimations (14.8%) and underestimations (10.4%) were located in the posture category adjacent to the correct one (Figure 27).

Classifications errors, ranging from 25.8% to 27.3% across the Saliency conditions, were very consistent with the overall location of errors in the study. 15.0% to 15.9% of classification errors were overestimations and 10.0% to 11.6% of the classification errors were underestimations in the different Saliency conditions (Figure 28).

The largest variability in the location of classification errors was shown in the evaluation of Body Segment. Classifications errors totaled 30.9%, 20.7% and 29.7% for Trunk, Shoulder and Elbow, respectively (Figure 29). Almost all classification errors for the Trunk were underestimations (26.8%). In contrast, classification errors for Shoulder (19.0%) and Elbow (22.4%) were mainly overestimations.

The locations of classification errors across the three levels of Repetition were comparable to those for the Saliency conditions, with errors of 28.0%, 26.5% and 25.0% for the 1st, 2nd and 3rd repetitions, respectively (Figure 30). As noted previously in section 4.3, the classification errors decreased progressively as repetitions increased. This is reflected in an increasing number of correct classifications from the 1st to the 3rd repetition (Figure 30).

Female and male participants performed similarly in terms of their correct and incorrect classifications (Figure 31). Their overall error rates and locations of errors were also comparable to those seen across Saliency conditions and repetitions.

The location of classification errors made by female and male participants was similar between the groups. From the total amount of classification errors made by the

Female and Male groups, 27.7% and 25.2% respectively, 16.5% and 14.9% were overestimations and 11.5% and 10.3% were underestimations; comparable to the location of classification errors for Salience Condition and for Repetition (Figure 31).

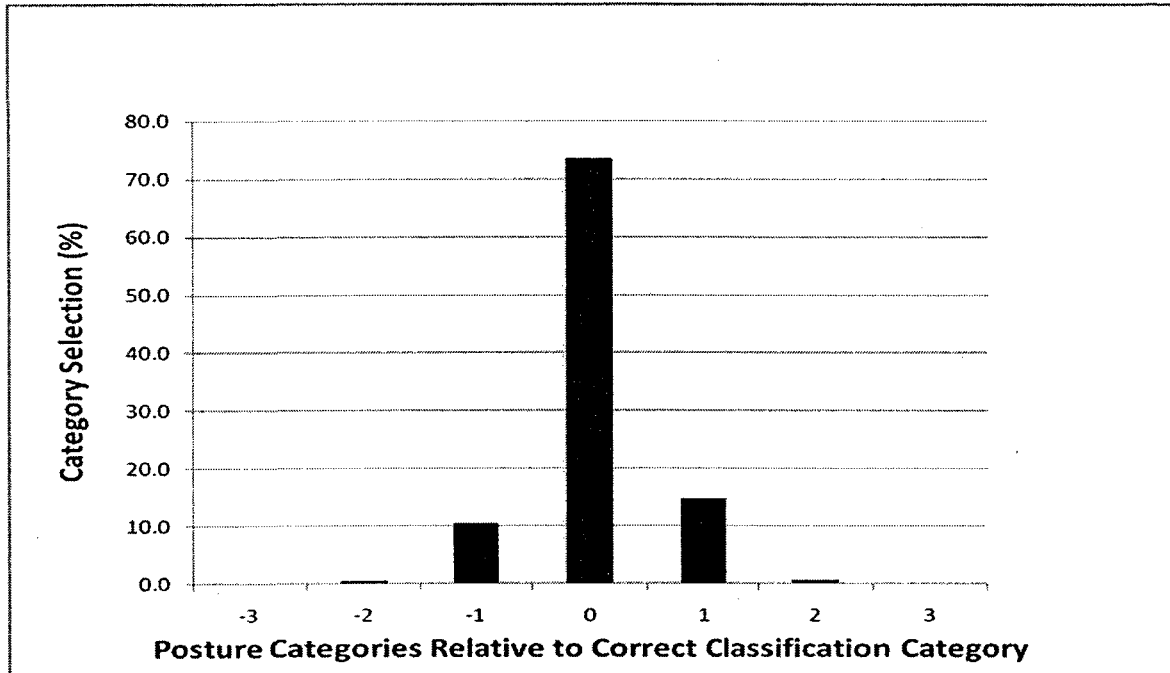


Figure 27. Overall distribution of correct classifications and classification errors. The number 0 represents the correct posture category for the classification. Numbers from -3 to -1 and 1 to 3 show the relative position of incorrect posture categories to the left and right of the correct posture category, respectively.

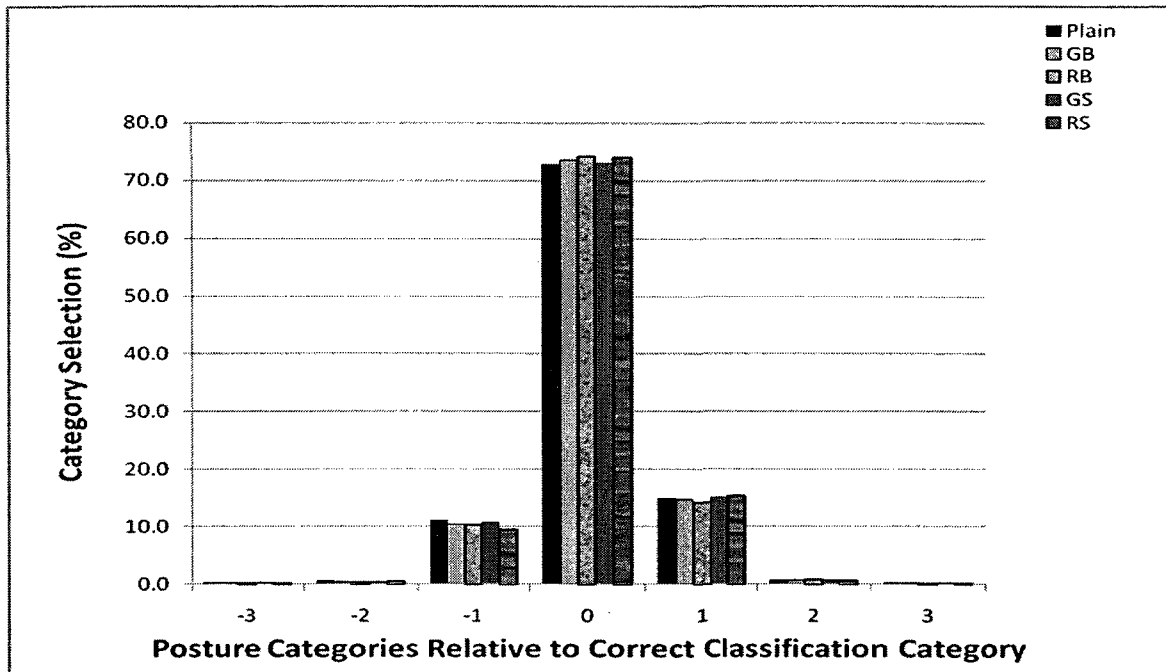


Figure 28. Distribution of correct classifications and classification errors by Saliency Condition. The 0 represents the correct posture category for the classification. Numbers from -3 to -1 and 1 to 3 show the relative position of incorrect categories to the left and right of the correct posture category, respectively.

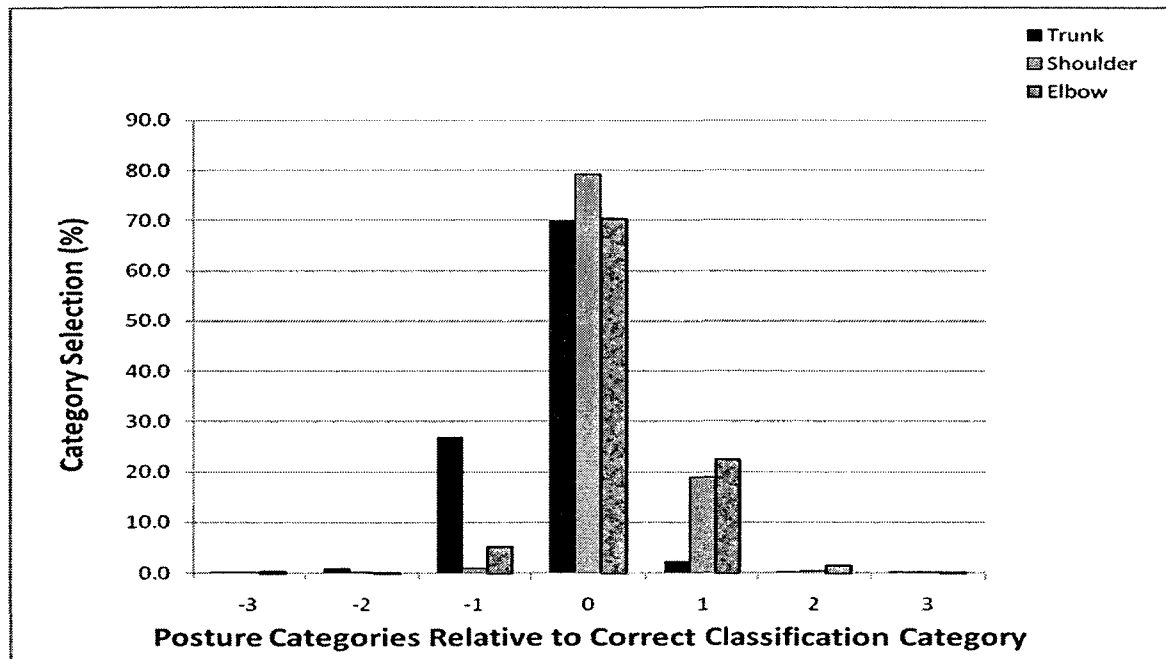


Figure 29. Distribution of correct classifications and classification errors by Body Segment. The 0 represents the correct posture category for the classification. Numbers from -3 to -1 and 1 to 3 show the relative position of incorrect categories to the left and right of the correct posture category, respectively.

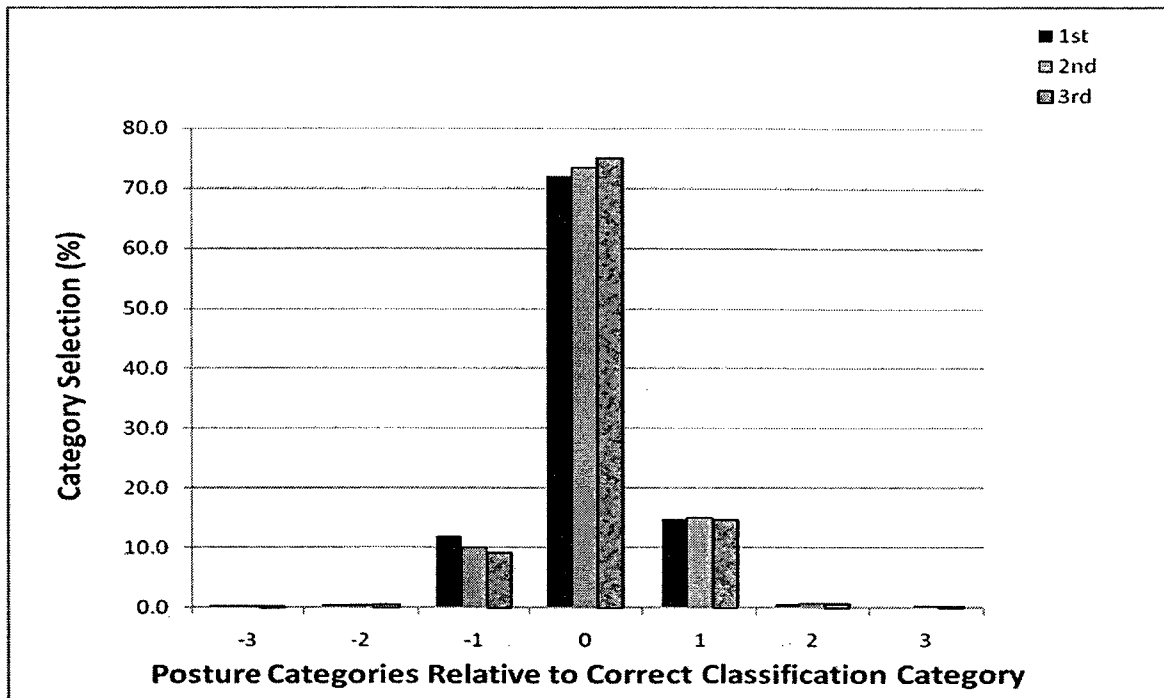


Figure 30. Distribution of correct classifications and classification errors by Repetition. The 0 represents the correct posture category for the classification. Numbers from -3 to -1 and 1 to 3 show the relative position of incorrect categories to the left and right of the correct posture category, respectively.

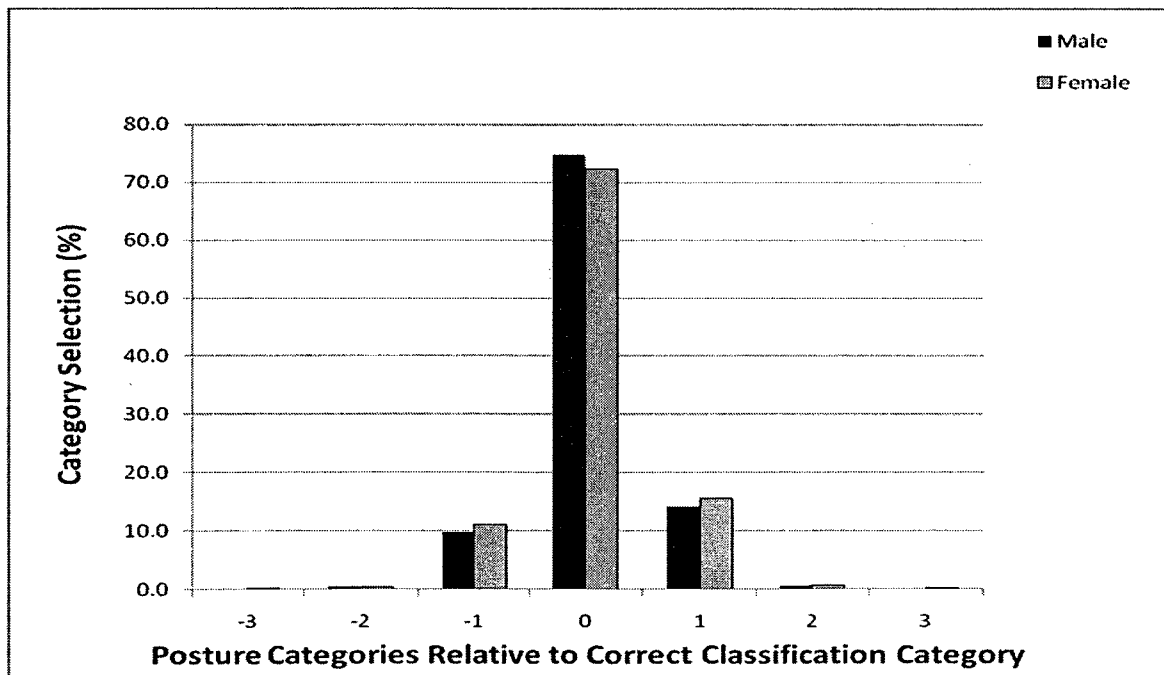


Figure 31. Distribution of correct classifications and classification errors by Gender. The 0 represents the correct posture category for the classification. Numbers from -3 to -1 and 1 to 3 show the relative position of incorrect categories to the left and right of the correct posture category, respectively.

Chapter V

DISCUSSION

Previous studies on analysts' performance using posture classification-based methods have shown that all participants make classification errors independent of their level of expertise (Andrews et al., 2008a). In general, the addition of salience to the posture categories in the diagrams positively influenced the performance of the analysts using the posture classification interface. Both measurements of performance in this study, decision time and error rate, were reduced when the posture categories were presented with a border, either achromatic (grey) or in colour (red). Also, overall, adding colour to the posture categories improved the performance of the analysts in regard to error rate, although the decision time was not significantly improved in the presence of red shading.

The presence of shading in the posture categories only reduced the error rates when the shading was red, but not grey. The participants' decision times were significantly reduced during their classifications when grey shading was present, compared to when the plain displays were viewed, but the error rates did not improve. Error rates were significantly reduced when classifications were made in the presence of red shading (compared to plain displays), but decision time did not improve.

In general, there was not as clear a trade off in the amount of time used by the participants to classify a posture and the classification error rates in this study, as compared to those reported in previous studies (Weir et al., 2007). Weir and colleagues (2007) suggested that the "expert" analysts in their study required more time to make

classification decisions and were also more accurate in their selections because they relied on previous knowledge of posture analyses. Andrews and colleagues (2008b) also related the experts' performance at posture classification to the use of serial or focused attentive perception while the novice analysts may have been using parallel or preattentive perception. Serial perception involves memory and requires more processing time, but leads to better discrimination of the visual targets, while parallel perception allows for shorter visualization of objects to categorize them according to their features (Enns and Rensink, 1990; Treisman & Gormican, 1988).

An inverse relationship between decision time and classification errors is suggested by Andrews and colleagues (2008b), who described that each increase in decision time of 1 s resulted in a reduction of error rate of 0.95% on average. A trade off between decision time and error rate was observed in the current study for GB and RB conditions and for the GS and RS conditions (Figure 32). An increase in decision time of 1.9% on average between GB and RB corresponded to a reduction of classification errors of 0.4% on average. Similarly, an increase of 2.3% in decision time between GS and RS was associated with a reduction of classification errors of 1.3%. This suggests that participants may have reduced their error rate by taking more time to classify postures when the colour red was present, compared to when only grey was present. The fact that the participants in this study did not have experience in posture classification indicates that the decisions were not performed based on previous classification knowledge, and were therefore not made during the serial perceptive stage, which requires the use of memory. However, after participants experienced the requirements of the task, they may have begun to use a more serial approach.

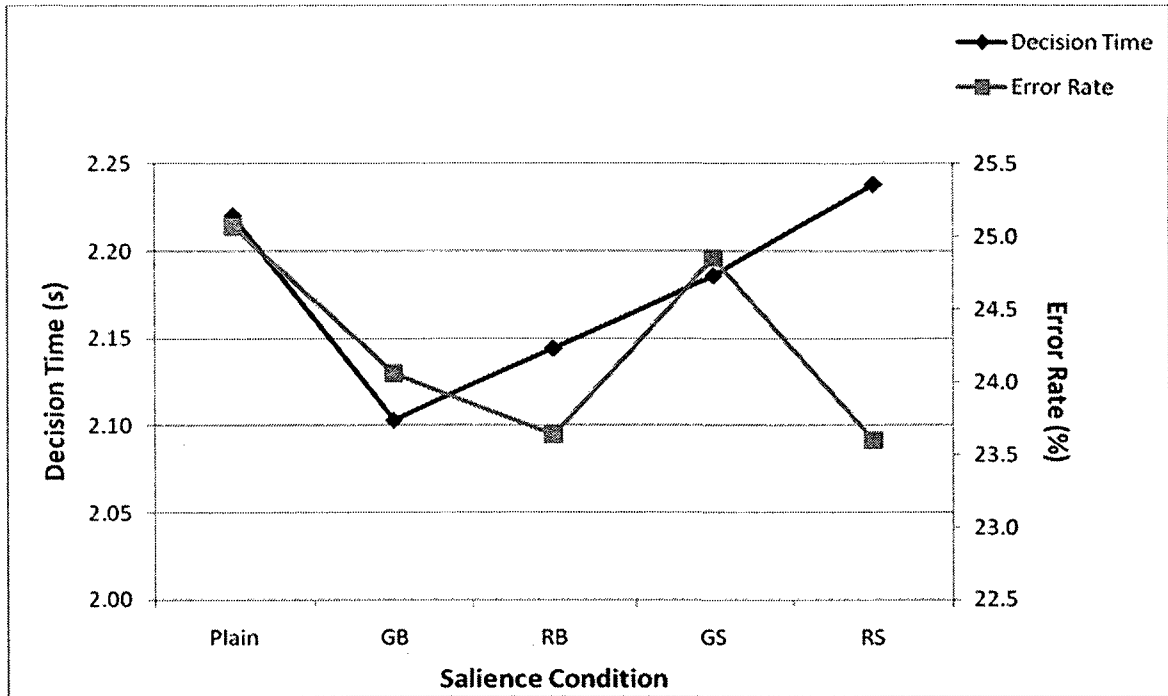


Figure 32. Comparison of the performance measurements, decision time and error rate, across Salience conditions [Plain, Grey Border (GB), Red Border (RB), Grey Shading (GS), Red Shading (RS)].

5.1. Effect of Salient Geometrical Elements on Decision Time and Error Rate

The first hypothesis of this study stated that showing the posture categories as closed objects and shading the areas defining the posture categories would reduce the decision time and the number of errors made by analysts, compared to their performance using the current 3DMatch visual display (Plain condition). The results of this study showed that the increased salience of the posture categories created by presenting them as closed objects with a grey border or a red border reduced classification time by 5.3% and 3.4%, respectively. Similarly, reductions in error rate of 1.0% and 1.4% were found for the same conditions. Therefore, the research hypothesis is supported for both decision time and error rate, when posture categories are shown as closed objects.

Grey shading of the posture category areas significantly reduced the classification decision time from the Plain condition, but when colour was added to the shading, no differences in decision time were observed. Error rates were reduced when red shading was added but not in the presence of grey shading. The research hypothesis is therefore not supported for both decision time and error rate, when shading is present in the posture categories.

A reduction in classification time of 5% is a significant timesaving if considered over long sampling cycles using video-based posture assessment methods. For example, for a 15-minute video clip, using 3DMatch, 2,700 static frames would be analyzed using current protocols (15 min x 60 s x 3 frames/s). This represents 32,400 posture classifications (2,700 frames x 12 combinations of body segments and views). Applying the average decision times obtained for the current 3DMatch diagrams (Plain condition = 2.22 s) and GB condition (2.10 s), a total reduction of 3,888 s, or approximately 1 hour of time savings would be realized if grey-bordered posture categories were used.

Changes to the accuracy of posture classification will have a direct effect on the calculation of low back loads from biomechanical models that utilize these postures to assess physical exposure (Andrews et al., 2008a). Overestimations of the postures evaluated in working tasks could result in those tasks being rated ergonomically unacceptable or unsafe for workers, requiring actions to modify the conditions or by adding personnel. Modifications made based on false positives may lead to unnecessary costs and/or a reduction of productivity. Conversely, consistent underestimations of evaluated postures can result in tasks being rated as ergonomically acceptable, when in reality, they may lead to workers' injuries or the development of MSDs (van Wyk et al.,

2009; Andrews et al., 2008a). Therefore, a reduction of 1% in error rate in the posture classifications (as seen in this study), whether they are overestimations or underestimations, represents a significant improvement that could ultimately lead to more precise biomechanical load outputs.

5.2. Effect of Shading as Salient Element on Decision Time and Error Rate

The second hypothesis of this study stated that shading would reduce the decision times and error rates, to a greater extent, than showing the posture categories as closed objects without shading.

The comparisons between the recorded decision times and error rates for grey and red borders and their corresponding shaded displays showed that decision time increased on average when shading was introduced. Error rates also increased when the analysts classified postures into categories accentuated with grey shading compared to when categories with only grey borders were displayed. There was also no significant difference in the error rates between classifications made from red-bordered and red-shaded categories. The research hypothesis in this case is therefore not supported for both measurements of performance.

It is possible that the shading applied to the posture categories introduced an additional asymmetry to the posture category boundaries, acting as a distractor instead of as the target object. Two geometrical elements were present in the shaded diagrams, borders and shading, which possibly caused a reduction in salience of the posture categories. Nothdurft (2000) suggested that the introduction of additional features could cause an increase or reduction in the salience of a target object. Although most combinations of features enhance the salience effect on performance, the improvement

may not be proportionally increased, and in some cases may also be reduced, when the number of salient features is increased. The closed borders of the posture categories already produced an asymmetry, whose salience may have been reduced by the presence of another salient feature, shading. The asymmetry between the target object and the surrounding distractors (i.e. the relationship between the posture category boundaries and the 0° and 90° axes) may have been compromised by the asymmetry between the boundaries and the shading of the posture category. Studies on the effect of asymmetry on visual search (Bodrogi, 2003; Nothdurft, 2000; Treisman & Gormican, 1988) observed that the addition of a feature to the target object may produce an additional asymmetry, with the surrounding distractors reducing the salience of the target object.

This explanation is reinforced by the comments about the shading made by the participants on the questionnaire. They reported that shading of the posture categories 'confused' or 'distracted' them.

5.3. Effect of Colour as Salient Element on Decision Time and Error Rate

The third hypothesis evaluated in the study stated that bordering and shading the posture categories in colour would reduce the decision time and the error rate to a greater extent than the same non-colour conditions.

The addition of colour to both grey conditions (GB and GS) resulted in significant increase in decision time of 2% and 2.5%, for RS and RB, respectively. An opposite trend was observed for error rate, where the addition of colour to the same achromatic conditions significantly reduced the error rate by approximately 1.2%, but only between grey and red shading. The research hypothesis was therefore not supported in terms of the

effect of colour on decision time. Support for the hypothesis was provided by the reduction in error rate when colour was added to the shaded posture categories.

In previous work, a coloured background was shown to have a considerable effect on the visual search of letters and numbers on a computer interface, reducing the search time by 15% over similar searching with grey background (Michalski & Grobelny, 2008). The lack of decision time improvement in the current study can be explained by the findings of Nothdurft (2000) who demonstrated that the addition of features to a target object can result in increases, reductions or even cancellations in salience. Similar to the effect produced by adding shading to the already existing borders of the posture categories, colour may add a considerable local asymmetry to the posture categories, thereby cancelling its salience effect.

It is also possible that the use of the colour red in the current study may have made the participants slow down, as the colour red is commonly associated with the need for caution. Being more cautious may have reduced participants' decision times and increase their attention to the task. This increased attention may have also lead to the lower error rates when the colour red was present. The results of this study, in regards of error rates, disagree with the findings of Michalski & Grobelny (2008) who reported that using colour backgrounds for letter and number search did not have an effect on the number of errors in the selection of such targets.

5.4. Effect of Body Segment on Decision Time and Error Rate

The results of the current study indicated that trunk postures were classified more quickly than shoulder postures, and elbow postures were classified faster than trunk and shoulder postures across Salience Condition and Repetition. The number of categories,

and therefore the size of the categories used to represent each body segment's range of motion, possibly had an impact on the decision time required for classifying the different segments.

van Wyk and colleagues (2009) evaluated the effect that the size of the posture categories had on analysts' decision time and argued that more decision time is required for a posture categorization as the size of the posture categories decreases. Smaller categories mean that more categories, and therefore more boundaries between categories, would need to be present to cover the range of motion for a given segment. Consequently, the faster decision times associated with the Elbow in the current study may be due to the fact that the elbow range of motion was represented by fewer categories that were larger in size (i.e. 5 categories) than those for Trunk or Shoulder (i.e. 6 categories each).

For the limited views provided in this study (i.e. flexion/extension), shoulder postures were classified with approximately 9% less error than elbow and trunk postures on average. Paquet and colleagues (2001) reported that the categorization of shoulder postures were more accurate than trunk or leg postures. They also found that the need for quantifying the angles between shoulders and hips to assess trunk postures added difficulty to the task and affected accuracy.

The images for shoulder postures in the current study always depicted the trunk in a neutral posture. Therefore, it is possible that the permanent vertical reference of the trunk in the posture diagrams helped the participants to estimate the shoulder posture angles more accurately. Although the neutral shoulder postures in the posture diagrams could also help categorize Elbow postures, the trunks may have obscured the vertical

reference provided by the arm. That could explain the higher error rate for the elbow postures. Paquet and colleagues (2001) observed that severe trunk flexion postures were estimated less accurately than mild flexion or neutral postures, which agrees favourably with the findings of the current study for trunk posture classifications.

5.5. Effect of Salient Elements on Decision Time and Error Rate in Regards to Body Segment

The fourth hypothesis presented in the current study stated that the effect that the salience conditions has on decision time and error rate would be the same when selecting a posture category for classifying trunk, shoulder flexion and extension, or elbow flexion movements.

The Salience x Body Segment interaction in the current study did not contribute to more than 1% of the total variance in decision time or error rate. Consequently, it was failed to reject this hypothesis.

5.6. Effect of Repetition on Decision Time and Error Rate

The observed reduction in decision time as the number of repetitions increased in this study suggests that participants underwent a training effect Weir and colleagues (2006) reported an improvement in novice participants' decision times and error rates after following a training protocol, which involved correctly classifying 25 posture images twice consecutively. Experiencing the same images three times in the current study possibly also resulted in a training effect, although no feedback was provided to the participants.

5.7. Effect of Repetition x Gender Interaction on Decision Time and Error Rate

Differences in performance between males and females were only observed in the interaction with Repetition. Moreover, there were only significant differences in the decision times of males and females when classifying postures for the first time. These differences were not found when the male and female participants classified the same posture image for the second or third time.

Bradshaw and Gates (1978) also showed a gender difference related to the effect of task repetition during a visual word search task. There was a significant difference in reaction times between females and males for the first exposure to the words in the experiment. This difference between females and males did not exist at the second exposure. The findings of the current study parallel those reported by Bradshaw and Gates (1978).

5.8. Gender as a Factor of Analyst Performance Related to Salience Condition

The last hypothesis of the study stated that female and male participants would perform equally in regards to decision time and classification error rate when selecting posture categories with different salience conditions.

The Salience x Gender interaction did not contribute more than 1% of the explained variance in decision time and error rate, therefore it was failed to reject this hypothesis.

5.9. Comparison of Perceived and Actual Salience Performance

The participants perceived the Plain condition to be the most difficult to classify. This perception paralleled the actual results of the Plain condition for decision time and error rate, as the Plain condition was one of the two Salience conditions (together with

RS) that had the slowest decision times and with the largest amount of classification errors (together with GS).

The participants perceived RB and RS to be the easiest Saliency conditions to classify with the fewest errors. This perception mimics the actual results on error rates for these conditions. The participants also perceived that the colour conditions (RB and RS) would lead to faster decision times among all Saliency conditions. However, the RB and RS showed slower decision times compared to the non-coloured borders and shaded conditions. Although the grey border condition resulted in the best performance overall, less than 10% of the participants rated it as easiest or quickest to classify, or the condition that would lead to the fewest errors.

It must be noted though, that the options on the questionnaire were not mutually exclusive. It was possible for a Saliency condition to be marked as both most difficult and fastest. Therefore, the questionnaire results must be considered with some caution.

The feedback provided by participants indicated that the repetition of the posture images helped with their speed and accuracy on the posture classification task. This completely agrees with the clear Repetition effect seen for both measurements of performance, decision time and error rate.

5.10. Magnitude and Location of Classification Errors

Overall, participants correctly classified more than 70% of the postures presented to them, despite not having any experience with posture evaluation tasks. Across all Saliency conditions presented in the current study, most of the classification errors were made in the posture categories adjacent to the correct category. Only about 1% of the total number of classifications was made outside of this range. These findings are

comparable with the results of previous studies (Andrews et al., 2008a; van Wyk et al., 2009) which found that, across conditions, 99% of the classifications were made in the correct posture category or ones immediately the adjacent to it.

Overall, more classification errors were overestimations (58.8% of all classification errors) than underestimations (41.2%). Similar distributions of errors were observed at each Saliency condition when the data were organized by Repetition and Gender. Previous studies by Andrews and colleagues (2008a) and van Wyk and colleagues (2009) reported a similar trend, with larger numbers of overestimations than underestimations, when classification errors were made.

However, when errors were expressed with respect to Body Segment, trunk postures were largely underestimated (88.9% of the classification errors), whereas shoulder postures and elbow postures were largely overestimated (91.8% and 75.5% of classification errors, respectively). Andrews and colleagues (2008a) showed that underestimations of trunk flexion postures occurred more often for moderate and severe postures; a trend which was also observed in the current study for flexion of the trunk greater than 60 degrees. Similarly, Lowe (2004) reported the tendency of shoulder abduction postures to be more frequently overestimated than underestimated. Genaidy and colleagues (1993) also found that participants tended to overestimate shoulder flexion postures, but only in the range between 1 and 60 degrees; postures greater than 60 degrees were mostly underestimated. Contrary to those findings, most of the classification errors, and certainly overestimations in the current study, occurred when shoulder postures of 32 or 67 degrees of flexion were classified.

5.11. Limitations

One of the trunk flexion images (i.e. 115 degrees) and one of the elbow images (i.e. 35 degrees) were not presented to participants in the middle of the range of the posture categories. This may have introduced a small increase in the error rate for those postures, since it has been shown that error rate increases as images are presented further away from the middle of the category and therefore closer to the category boundaries (Andrews et al. 2008a,b). This was viewed to be a minor limitation because the same images were presented to all participants and across all Saliency conditions.

An image representing 0 degrees of elbow flexion (straight forearm) was not available for this study. Instead, an image in 15 degrees of flexion was used. This image was classified incorrectly between 75.6% and 93.3% of the trials. This was considered a large limitation of the testing software, but because the same images were presented to all participants across all Saliency conditions, it may not have differentially affected saliency perception for the posture categories observed in this study.

In the current study, posture images were presented statically. In real analysis conditions, sequences of images on video can help analysts to classify images more accurately, by helping them better judge which posture would follow an observed posture in a particular movement sequence. This would likely assist them in classifying postures more accurately and at a faster rate than only having single static images to view. Although movement cues might only eliminate some classification errors, this limitation was consistent for all participants across the testing conditions.

All of the images presented in this study were of flexion and extension postures in the sagittal plane. Restricting the views to a single plane was necessary in order to keep

the study focused and manageable for the participants, in terms of the time needed to complete all of the classifications.

The participants in this study were university students with no experience with posture assessment methods. Some amount of classification errors was produced by this lack of experience. However, since the purpose of the study was to evaluate the effect of salience on posture categorization, the introduction of some degree of expertise might have confounded the results. Furthermore, previous studies on posture categorization (Andrews et al., 2008b; Weir et al, 2007; Weir et al., 2006) found no significant differences in terms of error rates between novices and more trained participants. Lastly, the number of participants tested in this study would have been drastically reduced if greater expertise was required. Collecting a larger sample was viewed to be much more important in terms of the generalizability of the findings. Given also that most analysts that perform posture assessments using tools such as 3DMatch begin with very little experience and are trained over time, testing untrained people was not viewed to be a major limitation.

The posture images presented to the participants showed a person modeling flexion and extension postures, without a shirt to allow for optimal posture perception. In real analyses, clothing may impair the perception of postures and may yield different results for decision time and error rates than those obtained in more optimal conditions in the lab. This was viewed as a minor limitation for the purpose of the current study, which intended to evaluate differences in perception in regards to salience. However, the use of images with models wearing work clothes would help to provide an estimate of performance during more real life conditions.

The computer lab printer was located in the area where the study took place. Brief access to the area was granted to non-participants during the experiment, when needed, with the warning that a study was being conducted. This may have caused minor distractions to some of the participants, influencing their decision time and error rates. It is suggested that the distraction that this might have posed for some participants is less than what would normally be present when analysts would work in a laboratory setting.

5.12. Future Directions

A study including trunk lateral bending and rotation postures, and shoulder abduction and adduction postures would round out the analysis of the effect of salience on the full range of postures available in 3DMatch.

The procedures used in the present experiment should be reproduced with actual users of video-based posture assessment methodologies in industry (e.g. ergonomists), given that they have significant relevant experience with these types of tools. Experience level may influence how the salience of the posture categories is perceived, and therefore may result in different performance outcomes compared to novices.

Future experiments including the salience conditions described in this study could evaluate different colours such as green or blue to evaluate the generalizability of the current study's findings related to colour.

The evaluation of participants exposed to training using the salience conditions presented in this study could also provide a greater perspective on performance related to posture category salience. Additionally, providing feedback after each block of trials or after each trial may also expose differences in categorizing postures using graphical interfaces such as 3DMatch.

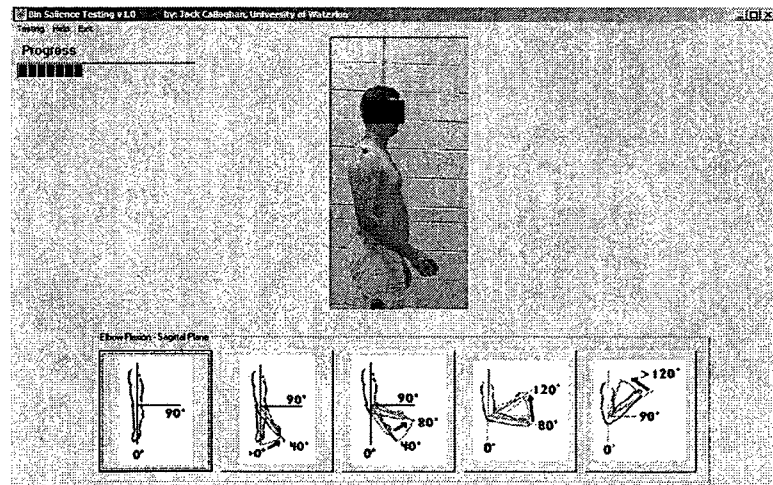
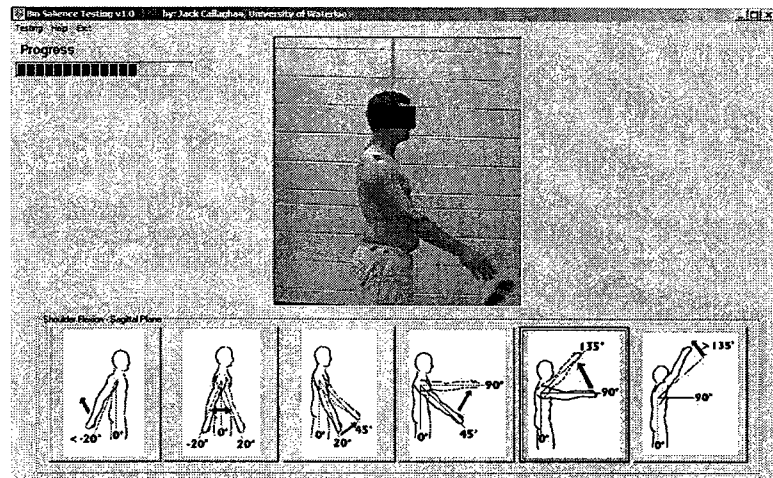
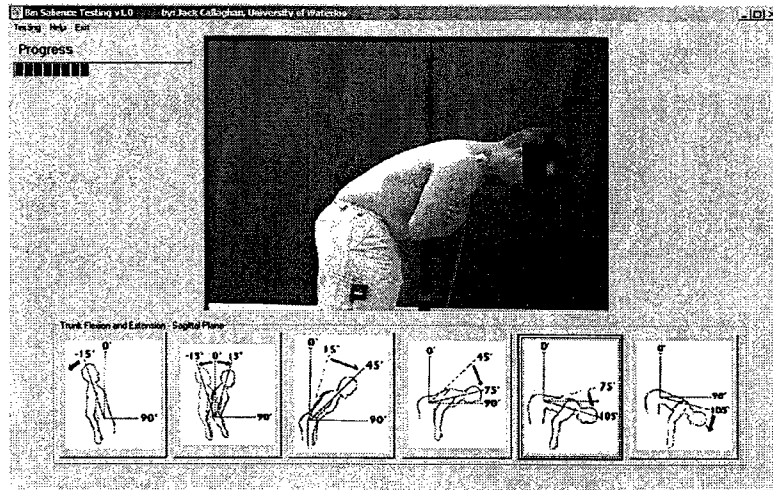
Chapter VI

CONCLUSIONS

It was the purpose of this study to determine if changing the salience of the posture diagrams currently used in video-based tools such as 3DMatch could improve analyst performance. Based on the results presented, it can be concluded that:

- Errors will always be made regardless of the Saliency condition.
- Errors and decision time can be reduced by adding a border, either achromatic or coloured, to the angle range shown in the posture category diagrams.
- The addition of colour to enhance saliency of the posture diagrams reduced error rates on average, compared to when the same geometrical achromatic displays were used.
- The grey border condition resulted in the best performance based on decision time and error rate combined.
- Adding a grey border would be a simple change that could be made to the current 3DMatch interface to improve analyst performance.
- The effect of repetition on decision times and error rates indicated that the performance of analysts improved as the exposure to posture classification tasks increased.

APPENDIX A



APPENDIX B

Subject code: _____

Faculty of enrollment: _____

Level of enrollment: Graduate Undergraduate

1. What posture diagrams (at the bottom of the screen) did you find the *easiest* to view?

Circle one.

- a. Plain (no shading, colour or boundaries)
- b. Those with gray boundaries (only)
- c. Those with red boundaries (only)
- d. Those shaded gray (only)
- e. Those shaded red (only)

2. What posture diagrams (at the bottom of the screen) did you find the *most difficult* to view?

Circle one.

- a. Plain (no shading, colour or boundaries)
- b. Those with gray boundaries (only)
- c. Those with red boundaries (only)
- d. Those shaded gray (only)
- e. Those shaded red (only)

3. What posture diagrams (at the bottom of the screen) do you think you selected *the quickest*?

Circle one.

- a. Plain (no shading, colour or boundaries)
- b. Those with gray boundaries (only)
- c. Those with red boundaries (only)
- d. Those shaded gray (only)
- e. Those shaded red (only)

4. What posture diagrams (at the bottom of the screen) do you think you selected *with the fewest errors*? **Circle one.**

- a. Plain (no shading, colour or boundaries)
- b. Those with gray boundaries (only)
- c. Those with red boundaries (only)
- d. Those shaded gray (only)
- e. Those shaded red (only)

5. Briefly describe the strategy that you used to select the posture diagrams during the study.

APPENDIX D

Tests of Between-Subjects Effects

Measure: Decision Time

Gender	1.361	1	1.361	1.708	.195
Error	70.100	88	.797		

Tests of Within-Subjects Effects

Measure: Decision Time

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Saliency	9.884	2.975	3.323	58.328	.000
Saliency * Gender	4.089	2.975	1.375	24.130	.000
Error(Saliency)	14.913	261.776	.057		
BodySeg	32.871	1.754	18.741	119.890	.000
BodySeg * Gender	11.379	1.754	6.487	41.501	.000
Error(BodySeg)	24.127	154.349	.156		
Rep	890.566	1.006	885.008	211.829	.000
Rep * Gender	28.178	1.006	28.002	6.702	.011
Error(Rep)	369.968	88.553	4.178		
Saliency * BodySeg	7.566	4.553	1.662	29.270	.000
Saliency * BodySeg * Gender	3.534	4.553	.776	13.674	.000
Error(Saliency*BodySeg)	22.747	400.672	.057		
Saliency * Rep	4.738	3.406	1.391	14.567	.000
Saliency * Rep * Gender	4.166	3.406	1.223	12.810	.000
Error(Saliency*Rep)	28.621	299.688	.096		
BodySeg * Rep	2.398	2.649	.905	17.767	.000
BodySeg * Rep * Gender	5.190	2.649	1.959	38.458	.000
Error(BodySeg*Rep)	11.875	233.114	.051		
Saliency * BodySeg * Rep	16.679	4.732	3.525	27.712	.000
Saliency * BodySeg * Rep * Gender	4.151	4.732	.877	6.898	.000
Error(Saliency*BodySeg*Rep)	52.964	416.382	.127		

APPENDIX E

Tests of Between-Subjects Effects

Measure: Percent of Error

Gender	176.998	1	176.998	.722	.398
Error	21567.353	88	245.084		

Tests of Within-Subjects Effects

Measure: Percent of Error

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Saliency	1519.656	3.569	425.782	18.668	.000
Saliency * Gender	357.541	3.569	100.177	4.392	.003
Error(Saliency)	7163.472	314.080	22.808		
BodySeg	75031.124	1.443	51982.212	95.869	.000
BodySeg * Gender	2517.516	1.443	1744.157	3.217	.059
Error(BodySeg)	68872.864	127.019	542.224		
Rep	7323.641	1.584	4622.982	69.139	.000
Rep * Gender	167.757	1.584	105.895	1.584	.212
Error(Rep)	9321.460	139.408	66.865		
Saliency * BodySeg	2766.882	6.333	436.903	13.813	.000
Saliency * BodySeg * Gender	594.780	6.333	93.918	2.969	.006
Error(Saliency*BodySeg)	17627.547	557.298	31.630		
Saliency * Rep	582.605	6.779	85.946	3.082	.004
Saliency * Rep * Gender	1679.316	6.779	247.733	8.883	.000
Error(Saliency*Rep)	16636.941	596.529	27.890		
BodySeg * Rep	2642.831	2.667	990.764	14.063	.000
BodySeg * Rep * Gender	739.428	2.667	277.202	3.935	.012
Error(BodySeg*Rep)	16537.840	234.737	70.453		
Saliency * BodySeg * Rep	1939.085	10.977	176.646	4.927	.000
Saliency * BodySeg * Rep * Gender	2353.869	10.977	214.431	5.981	.000
Error(Saliency*BodySeg*Rep)	34631.193	965.999	35.850		

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