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An Investigation of Boundary Associated Error in the use of Observation-Based Posture Assessment Methods

by
Tara Anjali Arnold

A Thesis
Submitted to the Faculty of Graduate Studies and Research 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

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2005
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Abstract

Background: Low back pain is a predominant problem in industry today, and is investigated through the use of posture matching tools, such as 3DMatch. Although posture matching tools are effective in delivering cumulative and peak loading estimates, they are not without problems. One such problem involves the accuracy of the posture matching process itself, and whether users make more misclassifications the closer a viewed image resides to a bin boundary. Purpose: The purpose of this study was two-fold; (i) To quantify the trunk posture misclassification error made as a function of angular distance from the posture bin boundaries, and (ii) To determine the effect these misclassification errors have on cumulative and peak low back load estimates from 3DMatch. The effect subject expertise had on posture matching ability was additionally examined. Tested variables included ‘degrees away from boundary’, ‘expertise group’, ‘view’, ‘repetition number’, and ‘position’. Methods: Forty-five male and 45 female subjects were recruited from the University of Windsor. All subjects went through the boundary testing program viewing flexion/extension and lateral bend images. Subjects were instructed to make quick and accurate bin selections, and collected data were used to determine the effect errors had on subsequent 3DMatch outputs. Results: Subjects made more errors the closer a viewed image was to a boundary for both views, and significant effects were found for view and position. Subjects made more errors in the flexion/extension than in the lateral bend view, and more in moderate and severe positions than in neutral. Overall, subjects were repeatable in their posture bin selections, and those bin misclassifications made were in bins adjacent to the correct bin in the majority of cases. A 13.5% difference was found between peak and cumulative loads
from the correct and incorrect analyses, excluding outliers. Conclusions: Therefore, subjects made more errors the closer proximity a viewed posture image resided to a bin boundary. Bin misclassification errors led to peak and cumulative load output errors when compared to analyses using correct bin classifications. Future Directions: Posture matching of other joints must be examined, as well as testing professional ergonomists, and testing images from real-lift situations.
Dedication

To my family, Rob, Romany and Crystal Arnold.
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Glossary

**Awkward/Non-neutral Posture:** any posture that deviates from the relaxed, neutral posture position. In this study, a neutral posture is defined as a posture in which the arms remain in the anatomical position, and the trunk is within the neutral range of -15 to +15 degrees of flexion and <15 degrees of lateral bend.

**Boundary:** a line dividing two posture bins/categories in a posture assessment software program.

**Cumulative Loading:** the loading on the body over time, as calculated by rectangular integration of the load/time histories.

**Location of Error:** refers to *where* an error was made, as defined by which bin was chosen in relation to the correct bin (e.g. 1 bin greater than the correct bin).

**Musculoskeletal Disorders:** all diseases of the muscles, connective tissues, and neural tissues that cause pain.

**Observation-based Video Methods/Tools:** observational methodologies involving the collection of posture data using a video camera, which is later analyzed using a variety of software packages.

**Peak Loading:** the maximum load on a structure during a period of time.

**Posture:** the position, attitude or inclination of the entire body, including the trunk as well as limbs (i.e. arms and legs).

**Posture Bin/Category:** the angle ranges that postures are separated into for analysis purposes in posture assessment software programs (e.g. 0-15 degrees, 15-30 degrees, etc.).
Chapter I - Introduction

Low back pain (LBP) is a predominant problem in industry today (Norman et al., 1998; Kumar, 1990; Punnett et al., 1991). In 2002, the highest percentage of claims resulting in time off work were back injury claims (29.6%) (WSIB Statistical Supplement, 2002). In addition to low back loading, posture has also been examined in relation to LBP development. Punnett et al. (1991) examined automobile industry workers, and discovered that back pain was associated with awkward trunk postures independent of force. Subjects who reported pain were five times more likely to work in mildly flexed trunk postures, and six times more likely to work in either severely flexed, twisted or laterally bent postures, than those who did not report pain (Punnett et al., 1991). Although many cases of low back pain had been reported, less than 3% of the examined postures were found to yield peak compressions of 3430 N, a value extremely close to NIOSH's Action Limit (Punnett et al., 1991). Low level cumulative loading may be the potential source of this pain for which no standard or limit currently exists.

Lifting standards have been established for peak loading, including NIOSH's compression Action Limit of 3400 N (Waters et al., 1993). However, injuries continue to persist in industry. Cumulative loading that occurs at sub-maximal levels over a longer time period is a potential explanation for such injuries (Kumar, 1990; Norman et al., 1998), as it has been shown to exist as a risk factor for low back pain. Cumulative loads on the lumbar spine have been found to be a good predictor of symptomatic osteochondrosis or spondylosis disorders of the lumbar spine (Seidler et al., 2001), as well as being linked to disc herniation during activities such as weight lifting (Seidler et al., 2003). Current research efforts are focused on developing a threshold limit for
cumulative loads, and all cumulative loading data collected are crucial in working
towards this goal. It is thus imperative that cumulative load outputs from posture
assessment methods are as accurate as possible (Sullivan et al., 2002). Quantification of
the errors in loads associated with posture misclassifications using such methods is an
important step in this process.

Peak and cumulative low back tissue loads are derived using biomechanical
models (e.g. Punnett et al., 1991; Keyserling, 1986; Callaghan et al., 2003), which are
often used in conjunction with observation-based posture assessment methods. Many of
these methods receive data inputs through a posture classification process known as
'posture matching'. This process involves matching postures from a video into the
appropriate posture category via a software interface. Several posture category options
(or bins) are given, and the user is required to determine which category the viewed
posture belongs in. Although widely used, this type of method is not without problems.
Misclassification errors can occur during this process, for the following reasons; the
visual discrimination required to complete the posture matching process (i.e. 'just
noticeable difference', or JND), the bin sizes employed, and the proximity of the viewed
postures to a bin boundary. These issues may subsequently affect peak and cumulative
loads calculated by a biomechanical model. These problems emphasize the importance
of examining these methods further.

It is important to know how small a visual discrimination can accurately be made
between two postures by a user, as fine discriminations must be made during the posture
matching process. The size of the discrimination that can be made dictates how small the
bin boundaries can be, while still allowing users to accurately differentiate between bins.
Weir et al. (2005) examined the usability of posture assessment methods from a user’s perspective by determining their visual sensitivity to trunk postural changes, or ‘just noticeable differences’ (i.e. JND) between two postures. Users viewed two trunk postures from a series of image pairs on a computer screen, depicting a person in either lateral bend or trunk flexion/extension postures. Users were instructed to determine whether the two trunk postures viewed on the side-by-side images were the ‘same’ or ‘different’. A user’s finest visual discrimination was defined as their JND. On average, direction was found to be an important factor with users most sensitive to postural changes in the ascending direction (JND average of 2 degrees) versus the descending direction (JND average of 7 degrees).

In addition to direction, other factors affect a user’s discrimination ability, such as expertise level. Novices have been found to attend to different attentional cues when compared with experts, and do not have the same magnitude of task-based memory representations that experts do (Starkes & Allard, 1993). These factors are problematic for judgment-based tasks, and could give experts an advantage when making such judgments. However, it has been found that subjects can train their perceptual sensitivity, which may serve to bring a novice’s performance level closer to that of an expert (Goldstone, 1994). Practice sessions involving categorization and identification have been found to enhance novices’ abilities to extract external information from such stimuli. Although training may help to increase novices’ discrimination abilities, each user in this study will only view three trials of each posture, which will most likely not be sufficient for training purposes.
The user’s view of the person in the image (i.e. flexion/extension versus lateral bend), can also have implications on their discrimination abilities. Subjects viewing people in flexion/extension postures have displayed a lower JND than those viewing people in lateral bend postures (Weir et al., 2005), implying that this factor affects users’ abilities to effectively discriminate, as well. Finally, users have been found to display higher JNDs when viewing people in severe postures versus neutral or moderate postures (Weir et al., 2005). The aforementioned factors will be factors of interest in the current study.

These JND-related findings have an implication for the size of the posture categories currently employed in many posture assessment methods. For example, in 3DMatch (Callaghan et al., 2003), the tool that will be used to test the second purpose in the current study, each flexion/extension bin or category is 30 degrees in size and the lateral bend bins range from 15–60 degrees. Research has demonstrated that users are capable of detecting postural changes much smaller than this (Weir et al., 2005), suggesting that the bin sizes could therefore theoretically be decreased. Although decreasing the bin sizes would yield more precise loading estimates from a biomechanical model, the user would have a larger number of bins to choose from, and thus a larger number of posture comparisons to make. A higher number of comparisons may result in more misclassification errors. Additionally, an increase in bin number would involve an increase in bin boundaries, which corresponds to more decisions that must be made by the user.

It is likely that a user will select an incorrect posture bin the closer the posture resides to a boundary. Although trained 3DMatch users have proven their ability to
consistently classify postures over time (Jackson et al., 2003), and low back loading outputs from 3DMatch have been in agreement with outputs from another biomechanical model (Callaghan et al., 2003), bin misclassifications are still a possibility. Callaghan et al. (2003) investigated the error which occurred from posture bin misclassifications to determine the magnitude of its effect (Callaghan et al., 2003). The largest cumulative moment error that occurred from one misclassified posture was 5.34%. However, further assessment of the errors in loading resulting from posture misclassification is necessary across a wider range of conditions. This study will investigate the error in cumulative and peak estimates associated with making bin misclassifications, and whether the magnitude of the error found warrants further adjustments to the tool.

It is apparent that low back pain is a problem in industry today (WSIB, 2002), and that methods do exist to quantify internal forces such as peak and cumulative low back loads that may lead to this pain. Ergonomists regularly make recommendations based on data from posture assessment methods in order to deem situations to be ergonomically acceptable or unacceptable for industrial workers (e.g. automotive plant operators). Therefore, it is imperative to examine if misclassification errors do increase when subjects’ actual postures reside in proximity to bin boundaries, and to quantify the effect that this error has on estimates of spinal loads, which are known risk factors for the reporting of low back pain in industry.
1.1: Statement of Purposes:

There are several parts to this study;

(i) The purpose of the Part I of this study was to quantify the number of trunk posture misclassification errors made (i.e. absolute and relative), as a function of the angular distance from the posture bin boundaries.

Note: Absolute error is defined as the total number of errors made. Relative error is defined as a percentage, relative to the total number of image trials seen in a specific condition.

(ii) The purpose of the Part II of this study was to determine the effect that the quantified bin misclassification errors had on cumulative and peak low back load estimates from 3DMatch, including joint compression and shear forces, and moments at L4/L5.

3DMatch analyses were completed on several video clips of people in flexion/extension and lateral bend postures. Once the error associated with bin misclassifications was quantified in Part 1, it was used to perform 'incorrect analyses' representing the types of errors subjects typically made over a range of situations. 'Correct analyses' were performed as well, with no bin misclassification errors made, and the cumulative load outputs from both analyses were compared.

(iii) A third purpose in this study was to determine the effect that subject expertise had on bin misclassification errors.

Error results were compared to determine if any of the three tested expertise groups, including Novice 1, Novice 2 and Expert, performed better than another. Expertise groups were chosen based on educational background and practical experience.
1.2: Statement of Hypotheses:

1.2.1: Hypothesis 1: As the angle between the person’s actual posture on the image and a bin boundary decreases, bin misclassifications (i.e. absolute and relative error) will increase (see hypothesized relationship in Figure 1).

The smallest JND on average found by Weir et al. (2005) was 2 degrees. This finding implies that some subjects are unable to differentiate between two postures if they are <2 degrees apart. Therefore, the closer an image resides to a bin boundary, the higher the probability that subjects will not be able to detect whether the posture is in the correct bin or the adjacent bin, and make a misclassification.

![Figure 1: Hypothesized relationship between the angular distance from the boundary and the number of misclassification errors made (e.g. for flexion/extension)]
1.2.2: Hypothesis 2: Novice subjects will make more bin misclassification errors (i.e. relative error), compared to Expert subjects.

*Experts have been shown to be more proficient than novices at the same task (Starkes & Allard, 1993; Goldstone, 1994).*

1.2.3: Hypothesis 3: Experts will display less variability than the Novice groups over the 3 trials viewed of the same posture image.

*Experts have more experience with the performed task, and will thus make less variable posture bin selections than novices.*

1.2.4: Hypothesis 4: Subjects viewing lateral bend postures will make more bin misclassification errors (i.e. relative error), compared to those subjects viewing flexion/extension postures.

*Subjects have been shown to display a larger JND when viewing lateral bend postures in comparison to flexion/extension postures (Weir et al., 2005), and thus need lateral bend postures to be further apart to perceive a difference. This indicates that subjects would have more difficulty perceiving which bin an image is in the closer it resides to a boundary, and would thus make more errors viewing lateral bend images.*

1.2.5: Hypothesis 5: Postures viewed which are severe (i.e. >45 degrees of flexion for flexion/extension, and >30 degrees of lateral bend for lateral bend) will elicit a higher number of bin misclassification errors, than those postures viewed which are neutral or moderate.

*Subjects have been shown to display a larger JND when viewing severe postures than neutral and moderate postures (Weir et al., 2005), and thus need two postures to be further apart to perceive a difference. This indicates that subjects would have more*
difficulty perceiving which bin an image is in the closer it resides to a boundary, and would thus make more errors viewing severe images.

Note: Posture categories are as follows for flexion/extension; neutral <15 degrees of flexion, moderate 15-45 degrees of flexion, severe >45 degrees of flexion. Posture categories are as follows for lateral bend; neutral <15 degrees, moderate 15-30 degrees, severe >30 degrees.

1.2.6: Hypothesis 6: The majority of bin misclassification errors made by subjects will be made one bin adjacent to the correct bin on either side.

Although it is possible for subjects to make bin misclassification errors in any bin, it is likely that the majority of errors would be made in adjacent bins. Based on all results of Weir et al. (2005), subjects' JNDs are smaller than the size of all bins employed in this study, signifying that subjects will typically be capable of choosing the next closest bin even if they are not capable of choosing the correct bin.

1.2.7: Hypothesis 7: The magnitude of cumulative low back loads (i.e. joint compression and shear forces, and moments at L4/L5) will be different for tasks that have been assessed when misclassification errors have been made by the investigator (based on results determined in Part 1 of this study), compared to when they are assessed without making any posture misclassification errors.
Chapter II - Review of Literature

2.1: The Role of Posture in Ergonomic Analyses:

2.1.1: Overview

Many observation-based video tools yield data outputs through a posture classification process known as posture matching. This process involves viewing a video clip of a person, and then choosing which category the person’s posture belongs in from a variety of choices. The possibility exists for misclassification errors during this process, emphasizing the importance of further examination of these tools to determine their accuracy. For the purposes of this study, ‘posture’ will be defined as the position or attitude held by the entire body, including the trunk as well as limbs (i.e. arms and legs). A neutral posture is defined as a posture in which the arms remain in the anatomical position, and the trunk is within the neutral range of -15 to +15 degrees of flexion and <+15 degrees of lateral bend. Any posture that deviates from this relaxed, neutral position will be termed an ‘awkward’ or ‘non-neutral’ posture.

Industrial work has been linked to low back pain (LBP) in the past (Norman, et al.; 1998; Kumar, 1990). In order to reduce the number of low back injuries which occur in industry, all potential risk factors associated with LBP must be considered. A considerable body of epidemiological evidence exists to suggest that awkward trunk postures and trunk kinematics are significantly linked to increased loads on the low back, and consequently to the development of LBP (Mirka et al., 2002). Marras & Mirka (1992) demonstrated that spinal loading increases with increasing trunk velocity during isokinetic contractions, and is further increased by asymmetric lifting (Mirka et al., 2002). Asymmetric lifting forces the body into non-neutral postures, which results in
significant increases in lateral shear forces in the back. Postures held by the body also affect the moments created by gravity acting on the center of mass of the trunk (sagittal plane), as well as in determining the muscle force needed to hold the adopted posture against the counter-acting forces of the trunk’s passive tissues (transverse and frontal planes) (Mirka et al., 2002). The further from neutral trunk position, the higher the internal muscle force that is required to hold this position, thus leading to added stress on the low back. Marras et al. (1993) suggested the ability of vertebral discs to withstand strain decreased when subjects adopted awkward postures. When the trunk was flexed, especially when flexion was combined with further awkward postures such as lateral bending and twisting, structural support from the facets was lessened. This increased disc fiber strain, and decreased the disc’s strain tolerance. Marras et al. (1993) also discovered that the risk of developing LBP in an occupational setting has been linked to a combination of variables, including lateral trunk velocity, twisting trunk velocity and sagittal flexion angle.

There are few results demonstrating the potential danger imposed by non-neutral trunk postures where no manual material handling (MMH) is taking place. Punnett et al. (1991) examined the possible relationship between non-neutral trunk postures and the risk of developing musculoskeletal disorders in the back. This case-referent study was conducted in an automobile assembly plant environment, and jobs with and without significant loads were studied to examine a wider variety of tasks requiring awkward postures. Postural demands of the jobs were analyzed and compared for the cases (i.e. workers with back disorders) and the referents (i.e. workers without back disorders). Trunk postures were classified as follows; neutral = < 20° of bending or twisting in any
direction, mild forward flexion = 21-45°, severe forward flexion = > 45°, and lateral bending or twisting = > 20° (Punnett et al., 1991). Peak biomechanical forces on the spine were analyzed, and the peak reactive torques for three back muscle groups and compressive forces at the L5/S1 spinal level were calculated using a 3-dimensional strength model. Punnett et al. (1991) found back disorders to be linked to awkward postures, such as mild trunk flexion, severe trunk flexion, and trunk twisting or lateral bending. The risk of injury increased with increasing number of non-neutral trunk postures, and increasing exposure duration (i.e. higher percentage of time spent in mild and/or severe trunk flexion). Finally, when the postural stresses analyzed were extrapolated to a full work cycle, the risk of developing a low back disorder was nearly four times greater than when assessed for lifting 44.5 N at least once every minute, demonstrating the great effect posture alone can have irrespective of lifting.

Trevelyan & Haslam (2001) have also linked musculoskeletal pain to poor and awkward postures for workers in the brick manufacturing industry. They found that the majority of musculoskeletal pain-related absences from work over the previous four years were due to back pain complaints. A high level of back discomfort reports were present in the discomfort survey filled out by the workers, as well. Further, several task elements forced workers into non-neutral postures, such as placing heavy loads onto trucks at an extremely low or extremely high height, forcing material handling either very close to the ground or the head, respectively. These postures place the back, as well as the wrists and arms, at risk for injury (Trevelyan & Haslam, 2001). Many of the workstations studied were also at too low a height for some workers, forcing a stooped or hunched posture that induced shoulder, neck and back pain complaints.
Workers in the furniture manufacturing industry have also been found to adopt awkward postures during work. When the jobs in this industry were ergonomically analyzed through injury records and survey results (Mirka et al., 2002), upholstery and machine room working were flagged as jobs with an elevated LBP injury risk. Following the ergonomic evaluation, high risk tasks were identified. These tasks included static non-neutral postures of extreme flexion > 50°, lateral bending > 20°, and twisting > 20° and repetitious bending/twisting for upholstery, and repetitious bending/twisting up to 5 lifts/minute, sagittal flexion > 80°, lateral bending > 15° and twisting > 45° for machine room working (Mirka et al., 2002). Once these postures were identified and ergonomic interventions were employed, Mirka et al. (2002) successfully improved the trunk postures and kinematics adopted to perform these jobs, and productivity benefits were even found in many cases.

In summary, the preceding studies have clearly demonstrated that awkward postures adopted by workers in industry are linked to the development of LBP. It is apparent that the adoption of non-neutral trunk postures by workers must be further investigated, and that the findings must be incorporated into ergonomic intervention plans to decrease their occurrence. Past studies have already shown that LBP is a product of non-neutral trunk postures, and the results of the current study will help determine whether these non-neutral postures are being accurately analyzed to yield correct low back loading outputs. If these outputs are compared to a person’s posture at the time of that output, accuracy in the output estimation is imperative for correct ergonomic analysis.
2.1.2: Posture Data Collection and Analysis Methods

Various methods have been used in the literature for the collection and analysis of posture data. Studies have been conducted in industry, as well as in laboratory and non-occupational settings. A variety of methods will be discussed in detail in the following section.

2.1.2.1: Pen-and-Paper Methods

Pen-and-paper based observational tools have been a commonly used method in the field of ergonomics. Paquet et al. (1999), as well as Keyserling et al. (1992), employed checklist methods to identify non-neutral trunk postures. Paquet et al. (1999) used PATH (i.e. Posture, Activities, Tools and Handling), an ergonomic assessment method that measures MMH exposure frequency in non-repetitious tasks, where Keyserling et al. (1992) used a one-page checklist to determine the ergonomic risk factors associated with non-neutral postures of the lower extremities, trunk and neck. Both groups examined industrial tasks, including iron workers, carpenters and labourers in the construction industry, as well as short-cycle warehouse jobs.

Paquet et al. (1999) and Keyserling et al.'s (1992) outputs differed, although they displayed similar points. Paquet et al. (1999) specifically examined what differences existed between jobs with respect to posture as well as some additional variables, and found that the MMH requirements of the varying jobs were very diverse, indicating the significance of task-based assessments for MMH exposures. Paquet et al. (1999) also found that the tasks performed and the workers themselves were important sources of variance, and that day-to-day differences in MMH exposure were the largest source. They suggested that the most reliable technique would involve evaluating multiple
workers over a longer period of time, as construction work tasks are non-repetitive in nature.

Keyserling et al. (1992) employed a quantitative computer-aided procedure, which accounted for percentage of cycle and overall time spent in various predetermined trunk and neck postures (Keyserling, 1986). They found that aside from the checklist displaying an increased sensitivity in the identification of awkward postures, it was generally comparable to another method, and awkward postures did exist in the studied environment. They concluded that their checklist method was an effective screening tool that could be utilized to identify cyclic jobs that force workers into harmful non-neutral postures. A negative point, however, was that the documentation from the checklist did not allow researchers to flag the specific task attributes that were putting the worker at risk for pain development. Although Paquet et al. (1999) studied non-repetitious jobs and Keyserling et al. (1992) examined repetitious jobs, a common thread in both sets of results exists; awkward postures do exist in industry and can be detected using a checklist procedure, but evaluating a job once with one checklist will not yield all the information required for an appropriate and accurate analysis; job specific analysis is required.

Lowe (2004) recently compared several pen-and-paper methods to the PEAK Motus optical motion capture system. Lowe’s system included 2 categorical scaling methods which estimated peak and mode (i.e. most frequently occurring) posture categories and temporal distribution of postures over a work cycle, in addition to a continuous visual analog scaling method which estimated peak and average postures for the elbow and shoulder. He found that the percent-error between the categorical scaling methods and the PEAK Motus system was high (i.e. average misclassification probability
= 64.9%), and that the percent-error between the visual analog scaling method and the PEAK Motus system was more reasonable (average misclassification probability = 30.1%) (Lowe, 2004). The errors that occurred were spatial and temporal in nature, and Lowe stated that they could be reduced through the use of a more sophisticated video-recording system that was capable of capturing multiple orthogonal video views for the video observed by the ergonomists while they employed their pen-and-paper analysis. A final result that has bearing on the current study was his finding that estimates of the elbow and shoulder postures were more accurate than those of the wrist and forearm obtained from a related study (Lowe, 2004). This finding agreed with those from previous studies of a similar nature (e.g. Li & Buckle, 1999), which have reported a relationship between joint segment size and accuracy of postural angle estimates (i.e. joints with smaller segments and thus high ranges of movement such as the wrist, were more difficult for the ergonomists to estimate the correct postures). In the current study, the posture of the trunk, a large body segment, is of primary interest, which may decrease the total number of posture misclassification errors that will occur.

RULA (Rapid Upper Limb Assessment) and REBA (Rapid Entire Body Assessment) are both pen-and-paper survey methods, used in workplace investigations where disorders have been reported (McAtamney & Corlett, 1993; Hignet & McAtamney, 2000). RULA users can quickly assess neck, trunk and upper limb postures, as well as external loads and muscle functions of a worker. The user chooses which posture category the worker is in for the neck, trunk, upper and lower arms, and wrists. Each category has a numerical score associated with it, and the scores are added up and used to find additional values in look-up tables supplied on the RULA score sheet.
The frequency of the job cycle is also taken into account, and a final grand score is calculated. Following the development of data collection methodologies and the scoring system, a scale of action levels was developed to indicate the level of risk as well as requirement for further assessments to be conducted (McAtamney & Corlett, 1993). The action levels range from acceptable conditions, to conditions necessitating further investigation and immediate change. REBA is applied in a similar way, only leg and wrist postures are included, as well. Look-up tables are supplied in REBA, and final scores are arrived at in a similar fashion, allowing the user to determine action levels (Hignett & McAtamney, 2000). RULA and REBA are attractive tools as they do not require any special equipment and are easily brought into industry. However, although a high consistency was found between subjects when examining posture category selection, discrepancies occurred when body segments (i.e. specifically the lower arm) resided near category borders (McAtamney & Corlett, 1993). Bin boundary proximity is the primary focus of this study.

The main advantages of pen-and-paper methods are that they are an inexpensive means of data collection, and allow for posture assessments to be carried out with minimal equipment and with minimal disturbance to the worker (Li & Buckle, 1999). However, the optimal number of observations required for the best results varies depending on many factors (e.g. duration of task, frequency of task, repetitious vs. non-repetitious cycles, etc), and the criteria for determining such a number remains unclear. This implies that there is room for improvement when employing such processes to render the data collected in this manner more accurate (Genaidy et al. 1994). Several researchers have stated that data obtained by pen-and-paper methods are not reproducible.
when they are used in dynamic work situations, as many of them are in plants and in the laboratory, and the intra- and inter-observer variability can be high (Li & Buckle, 1999). For this reason, it is preferred that pen-and-paper based tools are employed when subjects are maintaining static postures for longer periods of time, or when the work pattern is simple and repetitive in nature. Finally, although awkward posture is an independent risk factor for LBP development (Punnett et al., 1991), it also interacts with additional factors such as loading, vibration and psychosocial factors to produce combined effects related to MSD development (Waters et al., 1993). Basic pen-and-paper methods do not typically allow for the simultaneous consideration of these factors, and it is not yet known how these factors should be weighted in order to compare their combined effects appropriately (Li & Buckle, 1999).

2.1.2.2: Observation-Based Methods

Juul-Kristensen et al., (2001) compared results from a video-based observation method to those from direct technical measurements such as inclinometers and electrogoniometers. They examined postures and movements in repetitive tasks in a poultry processing plant. They discovered that when comparing the use of observation methods versus direct measurements, the observation method tended to be more rudimentary and displayed a lower accuracy compared to the direct measurement techniques. This difference was especially notable when the dynamic nature of the work was considered. They concluded that the two methods complemented each other well; the operation of the inclinometers and electrogoniometers resulted in measurements of angles, velocities and accelerations, and the observation method measured additional variables related to work organization. However, Juul-Kristensen et al. (2001) did admit
that although direct measurement may yield more accurate results, observation methods were best for field studies as the equipment and technical requirements are less for these methodologies.

Keyserling (1986) tested a video-based observation method similar to the method that will be used for addressing the second purpose of this study. The method was video-based and was used to analyze and describe trunk and shoulder postures of automobile assembly workers. He videotaped workers to create a permanent record of the jobs they performed, and the data input and time-keeping analysis tasks were completed by a computer. Postures were analyzed by classifying them into categories or ‘bins’, which provided an easy method for identifying non-neutral postures that could be leading to back and shoulder disorders (Keyserling, 1986). This system yielded outputs that described the amount of time spent in each posture category by each worker. The purpose is similar in nature to engineers’ real-time direct-measurement techniques used to determine the amount of time required to perform a job, only in this instance, the amount of time spent in each binned posture was measured. This system was deemed successful, as highly reproducible findings were reported, intra- and inter-observer reliability were high, and the findings were comparable to a similar study. Keyserling concluded that a crucial tradeoff existed between the cumbersome and lengthy data analysis process and the level of detail incurred by this type of analysis (1986). He deemed his system much less time consuming than existing posture analysis methods, rendering this video-based observation method attractive for use.

Several case-referent studies that reported the use of observation-based methods have been conducted, and produced comparable results. Neumann et al., (2001a)
examined automotive assembly plant workers in an attempt to test a new sampling approach's ability to identify LBP risk factors. One of their main findings was that, among other variables, trunk kinematics results were significantly different between cases and referents, and thus deemed posture a risk factor for LBP development. Regarding kinetic variables, peak as well as cumulative spine loads were considered viable risk factors, as well (Neumann et al., 2001a). Another study by Neumann et al., (2001b), sought to test a video-based posture assessment method that was used to determine if associations existed between the trunk kinematics measured (i.e. trunk angles and angular velocities) and LBP reporting. They discovered that trunk flexion variables such as peak angle, peak velocity, average velocity indicators, and percent time in flexion category were all significantly different between cases and referents. Further, extreme trunk flexion and trunk flexion velocity were strongly linked to higher risk of LBP development (Neumann et al., 2001b). In combination, these studies demonstrate that non-neutral postures, with or without the handling of a significant load, are an important risk factor for the development of LBP (Neumann et al., 2001a; Neumann et al., 2001b; Punnett et al., 1991).

3DMatch is another observation-based posture assessment method using video, which yields, among other outputs, acute and cumulative loading exposure estimates in 3 dimensions at the L4/L5 spinal level (Callaghan et al., 2003). 3DMatch was created with the aim of including the accuracy and validity of biomechanical modeling, while also being a relatively fast and inexpensive tool that allows for the analysis of tasks in 3-dimensions from 2-dimensional video footage. It is practical for ergonomists to employ in an industrial setting for repetitious tasks due to minimal equipment required on-site.
during data collection, and data analysis requires only video capturing software and a computer. Limited subject-specific information needs to be input into the program (e.g. age, subject code, gender, mass and height), and a posture matching technique is employed that describes the subjects’ postures over the course of the data collection period. The image from the video appears on the interface screen, the user observes what posture the subject is in, and then chooses the appropriate posture category from a range of selections. The user also enters any hand loads present. The tool includes a three-dimensional rigid link segment model that incorporates single muscle equivalents and a third order polynomial model (McGill et al., 1996). The model calculates reaction forces, moments at L4/L5, bone-on-bone forces, and several kinematic variables including degrees of trunk flexion, percentage of time spent in flexion, etc.

The 3DMatch categories are independent of, although similar to, those employed in other approaches. For example, Punnett et al., (1991) employed 3 categories of -20–20 degrees, 20-45 degrees, and >45 degrees for flexion/extension. Keyserling (1986) employed the same categories, along with an additional category of <20 degrees. The flexion/extension categories used in 3DMatch are -15-0 degrees, 15-15 degrees, 15-45 degrees, 45-75 degrees, 75-105 degrees, and >105 degrees. However, when classifying postures as being ‘neutral’, ‘mild’ or ‘severe’, 3DMatch categories are similar to those from Punnett et al. (1991) (i.e. neutral = <20 degrees, mild = 20-45 degrees, severe = >45 degrees). For lateral bend, Punnett et al. (1991) and Keyserling (1986) both used a category including 20 degrees in each direction away from 0 degrees. 3DMatch employs lateral bend categories of 0-15 degrees, 15-30 degrees, and 30-90 degrees in each direction, and are classified as neutral, mild and severe, respectively.
Advantages of using 3DMatch include the minimal equipment required for data collection, with only one video camera and a force gauge to collect hand loads or forces. Although data processing programs can be expensive to purchase, the data analysis program itself and additional equipment (i.e. the video camera) can be relatively inexpensive considering that they are one-time purchases. The processing and analysis time is decreased by decimating video clips to 3Hz (Andrews & Callaghan, 2003) before they are input to 3DMatch as AVIs. Initial validation tests demonstrated high intra-observer reliability (Jackson et al., 2003) and relatively accurate results in comparison to results from a validated biomechanical model (Callaghan et al., 2003). Moreover, should a discrepancy exist later on in the process, the user can go back to the original AVI files to see exactly what the subject was doing at any given time.

The main attraction of using observation-based video methods in field settings is the minimal amount of equipment that is required for data collection processes (Li & Buckle, 1999); a video camera is the main piece of equipment that is necessary. In addition, the use of a video camera can avoid observer bias since an investigator does not always need to be present during the actual recording period. If a camera is set up to record an entire working area, the investigator’s presence is not required, and the potential for any unusual worker behaviour that occurs from being watched is eliminated. This is not always the case however, depending on the job being recorded. The investigator may have to follow the subject to several different locations to record all parts of their job. The primary negative aspect of video-based analysis systems is the amount of time required to analyze the data. In addition to the analysis time itself, people must also be recruited and trained to perform the analysis procedures correctly. Another
issue is that analysts have been found to incorrectly identify postures that belong in adjacent posture bins (e.g. placing a ‘non-neutral’ posture into a ‘neutral’ bin); these mistakes obviously lead to inaccurate results (Weir et al., 2005; Callaghan et al., 2003; Jackson et al., 2003). However, as mentioned previously, these errors seem to occur more in the selection of elbow and wrist postures (i.e. smaller body segments), where neck and trunk postures have been evaluated more accurately (Keyserling, 1986; Li & Buckle, 1999). Finally, sometimes it is difficult to be granted permission by plant management and union representatives to videotape workers in a plant setting.

2.1.2.3: Electromagnetic Method

A final method of data collection to be noted is an electromagnetic tracking device that collects positional data from four sensors in real time. Through the use of this system and a regression-based static biomechanical model (Potvin, 1997), compression at the L4/L5 spinal level can be estimated in real time (Agnew et al., 2003). Other studies have attempted to link awkward postures to injury statistics (Punnett et al., 1991; Keyserling, 1986), and future work employing video-based observation methods will strive to link posture, as well as cumulative loading to injury. For this reason, the following methodology is worth discussion.

Agnew et al. (2003) sought to develop a method to document cumulative loads inherent in lifting tasks, at the low back level in real time. A simple regression based biomechanical model was used, and the model software created was employed with an electromagnetic posture tracking device (Fastrak®). Agnew et al. (2003) tested the Fastrak® system against outputs obtained from a dynamic link segment biomechanical model to determine its’ ability to predict cumulative loads. They discovered that their
method yielded results that were comparable with those obtained from other cumulative load studies, and that far less data processing time is required since the Fastrak® yields positional data, and with the use of the custom software, results in low back loads, immediately following task completion. Agnew et al. (2003) concluded that the Fastrak® system was useable for future lab-based lifting and lowering studies due to the reduced data collection and processing time related to its use. However Fastrak® emits an electromagnetic field which compromises the device’s measurement accuracy when in the presence of metallic objects and electromagnetic noise, both of which exist in factory settings. Therefore, although the Fastrak® decreases the data analysis time requirements necessary to estimate cumulative low back loads, and therefore addresses the main downfall of video-based observational techniques, it is still not an appropriate method for data collection in most industrial environments.

2.2: Sensitivity of Posture Perception (Just Noticeable Differences: JND):

2.2.1: Overview

The task to be completed in the current study requires subjects to identify what range a posture falls in by viewing a video image of a person on a computer screen. This task is dependent on a user’s ability to perceive a posture correctly, and to accurately estimate which of the given posture categories the viewed posture belongs in. The main issue with tools that rely on these perceptions is that it is unknown how well people can perceive a given posture, and accurately classify it into a category. Studies have been carried out examining peoples’ abilities to differentiate between two stimuli or postures (Downing, 1988; Nicholson et al., 1997), however, little work has been done regarding
peoples’ abilities to accurately match viewed postures into categories, or in evaluating the ramifications of the category misclassifications that occur.

Several factors affect a user’s JND, including those internal or inherent to the subject such as age, previous learning experiences, boredom and fatigue, and external factors which are attributed to the surrounding environment or experimental conditions themselves. Examples of these are ambient temperature, order effects, and testing techniques (Nicholson et al., 1997).

Level of expertise has been an important variable of interest in discrimination testing. Charness (1989) stated that familiarity and practice with a task are necessary for performance, but more that this is required for skilled performance. This statement indicates that ‘novices’, or individuals who have little or no prior experience with a task, are still able to perform it, possibly following some type of training. Novices, however, are usually at a slight disadvantage since they are only able to base judgments on sensory information directly from the image, and possess less semantic representations of the images than experts (Clancy & Hoyer, 1993). In contrast, medical experts, for instance, are able to access semantic information that stimulates detection of domain-specific stimuli. Charness found that this ability led to quicker, more accurate responses in comparison to novices when given several visual-cognitive tasks requiring discrimination (Clancy & Hoyer, 1993).

Additionally, it has been shown that animals as well as humans will better perform future tasks involving a stimulus that they have had previous exposure to (Goldstone, 1994). This finding implies that, although experience gives a distinct advantage, training novices to give them experience should lead to their improved task
performance. Novices have also been shown to be at a disadvantage in other situations, as well. In tasks where subjects are forced to categorize two images or objects as being the ‘same’ or ‘different’, perception has not been found to be the only component required. Higher level cognitive functions are involved as well, including memory and attention (Goldstone, 1994). Novices have been shown to attend to different attentional cues than experts, and they do not have nearly the magnitude of task-based memory representations as compared to an expert (Starkes & Allard, 1993); these factors are problematic for such judgment-based tasks, and could give experts an advantage when making such judgments. However, following training involving categorization and identification of stimuli the ability to extract external information increased (Goldstone, 1994). Once again, training seems to be a potential method to increase novices’ discrimination abilities, and close the gap between them and experts.

Furthermore, experts and controls have been found to display more accurate results for easier (i.e. two obviously different postures) versus more difficult postures (i.e. two postures that are very similar) (Downing, 1988). Finally, novices have not been shown to perform more poorly than experts due to their inability to conceive the task, but rather due to perceptual limitations (Saffell & Matthews, 2003). This implies that once subjects have learned to perceive appropriately, they could cognitively perform the task at hand. For this reason, level of expertise will be an important variable of interest in the current study. This study will examine whether expertise level differences are prevalent during bin selections by examining the occurrence of errors close to bin boundaries.

Weir et al., (2005) conducted a study pertaining to the usability of posture matching methods from a user’s perspective. Specifically, the user’s sensitivity to trunk
postural changes, or "just noticeable differences" (i.e. JND), between two postures, was examined. Their subjects were asked to observe two trunk postures from a series of image pairs on a computer screen, where the person shown was performing either a lateral bend or a trunk flexion/extension motion, in an ascending or a descending direction. Postures were presented to subjects in a random block in one degree increments. The subjects were instructed to determine whether the posture images seen were the 'same' or 'different'. A subject's JND was determined once they made a 'different' selection, and this was deemed the finest discrimination that could be visually made. Weir et al. (2005) discovered that subjects overall were most sensitive to postural changes in the ascending direction (JND average of 2 degrees) versus the descending direction (JND average of 7 degrees).

Nicholson et al. (1997) utilized the Weber fraction to quantify discrimination, and discovered that when comparing subject's manual stiffness perception when palpating a spine mock-up device, the mean Weber fraction was 7.71%. This value indicated that 7.71% was the smallest magnitude difference between the two spine postures that led to an accurate discrimination of 'different' between the two. A smaller Weber fraction indicates a greater ability to identify fine discriminations between two stimuli. In another experiment involving stiffness stimuli, the average threshold required for discrimination was 11.5% (Nicholson et al., 1997). Although not directly comparable to the JND values from Weir et al. (2005), due to the different quantification methods employed and different types of tasks, both studies indicate that an observer is capable of accurately discriminating between two stimuli, even if only a fairly small difference exists. Should these findings be reiterated in the current study, and show that even when an image
resides in close proximity to a bin boundary subjects are able to correctly classify that image (i.e. small difference between two stimuli), perhaps no alterations need to be made to the current methods of posture matching.

2.2.2: Issues with Incorrect Posture Perception (Bin Misclassifications):

It is apparent from the aforementioned studies that people are capable of finely discriminating between two stimuli or postures. These findings have a major implication for currently employed methods using posture matching. Specifically, they may impact on the bin sizes currently employed in the 3DMatch program that will be used in this study. Although it appears that posture bin sizes could be reduced in order to yield more precise tissue load outputs, negative outcomes would also likely result, such as an increased number of bin misclassifications. A bin misclassification involves a user selecting an incorrect bin to depict the posture that the viewed subject is actually in, and these misclassifications may lead to inaccuracies in peak and cumulative low back loads outputted from a biomechanical model.

Currently in 3DMatch, the flexion/extension bins are 30 degrees in size and the lateral bend bins range in size from 15–60 degrees. If users are capable of discriminating between postures that are, on average, 7 degrees apart (Weir et al., 2005), the 3DMatch bins could be made much smaller. This change would increase the accuracy of the outputted load measurements. Currently, the midpoint of the selected bin is input into the model for purposes of estimating load. For example, a posture selection of -15 degrees of trunk flexion and one of 15 degrees of trunk flexion, are both assigned a value of 0 degrees of trunk flexion for the purposes of the model calculations. Therefore, regarding these calculations, a person in completely erect trunk posture of 0 degrees of flexion will
yield the same cumulative loading estimate as a person in a trunk flexion posture of 15 degrees, or even greater than 15 degrees if a bin misclassification is made and the posture is placed in the next highest bin. Smaller bin sizes would slightly decrease the magnitude of this inaccuracy, as the midpoint value inputted into the biomechanical model would be incorrect by less than 30 degrees if a misclassification error was made.

Although decreasing the bin sizes might yield more accurate spine loading estimates, a reduction in the bin sizes will increase the number of bins to choose from, and therefore increase the number of posture comparisons that must be made by a user. As a result, there will be an increased likelihood that posture misclassifications will occur. Lowe (2004) found that when comparing results from two category scales to an optical motion capture system, that the three-category scale yielded misclassifications 30.1% of the time, and the six-category scale yielded misclassifications 64.9% of the time. Secondly, the larger number of posture comparisons would increase data analysis time and worsen the already intensive process (Keyserling, 1986). It is probable that posture misclassifications can greatly affect the associated cumulative and peak loading estimates, rendering it imperative that bin misclassification errors are minimized as much as possible.

Postures that reside in close proximity to bin boundaries are also problematic for users. There is a higher likelihood that a user will select an incorrect posture bin the closer its proximity to a boundary. Discrimination is fairly constant over the average range of stimuli, but tends to deteriorate at extremes, such as boundaries (Nicholson et al., 1997). Downing (1988), while examining perceptual sensitivity, found that sensitivity to detect differences in stimuli decreased dramatically when the stimuli were
close together. If the stimuli, or postures in this study, were near the middle of a posture bin, it would not matter for the purposes of the model employed in 3DMatch if the user thought the subject was in 5 versus 8 degrees of flexion; either selection would be in the correct bin. However, if the subject was in 14 degrees of flexion and the user perceived them to be in 17 degrees of flexion, they would select the next highest bin by mistake (i.e. 15-45 degrees of flexion instead of -15-15 degrees of flexion). The ramifications of this posture bin misclassification would produce an incorrect cumulative loading estimate. A value of 30 degrees of trunk flexion (i.e. midpoint of the next highest bin = 30 degrees) would be input into the model instead of the correct bin midpoint of 0 degrees. It is imperative to determine how close a posture must be to a bin boundary for a misclassification to occur, so that methods such as 3DMatch can be evaluated for accuracy. It is also important to determine what the differences are in peak and cumulative load estimates should a posture bin misclassification occur.

2.3: Posture Bin Boundaries:

One of the main problems with video analysis that involves a posture matching protocol is that bin misclassifications can occur near the bin boundaries (Godin et al., 2004). A user’s ability to accurately discriminate between two images deteriorates at extremes of a range (Nicholson et al., 1997), such as at the bin boundaries of posture categories. If a subject’s posture is in close proximity to a boundary, and the user is unable to correctly categorize the subject’s posture (i.e. due to an inability to appropriately compare the two when they are close to a boundary), errors will result. Although trained 3DMatch users have shown high intra-user repeatability of posture selections over several test days (Jackson et al., 2003), and the results obtained were in
reasonable agreement with those from a biomechanical model (Callaghan et al., 2003), it still remains that errors will occur, and should be quantified systematically.

The amount of error in cumulative loading estimates which occurs from a single bin misclassification, has been investigated to determine the severity of this issue (Callaghan et al., 2003). Callaghan et al. (2003) found that the largest cumulative moment error that occurred from one misclassified trunk flexion posture for a sagittal lift was 5.34%. This error, however, was only over a 16 frame period, which is just over 5 seconds of video tape when analyzing at 3Hz (Andrews & Callaghan, 2003). However, analysis done using these types of methodologies could occur over a much longer time period. For example, several recent studies employing 3DMatch have examined 2 hour video tapes (Godin et al., 2004; Godin et al., 2004). Much higher percentages of misclassification could occur in these long records, resulting in higher overall error (Callaghan et al., 2003). Should the misclassifications occur in different directions, it is possible they would cancel each other out (Callaghan et al., 2003).

It is thus imperative to examine if errors do increase when subjects’ postures reside in close proximity to bin boundaries, and then to quantify the effect this error has on estimates of low back spine loads. Ergonomists make recommendations based on data from these types of tools, as well as deem situations to be safe or unsafe for workers. If a significant amount of error is occurring during these data analysis processes, recommendations could be adversely affected. For example, if overestimations were made during posture matching, these errors would be reflected in all model outputs, such as peak and cumulative loading estimates. If the cumulative load estimates are high in comparison to previous work, or if the peak load estimates are high in comparison to
known limits (e.g. NIOSH; Waters et al., 1993), this type of activity would be deemed unacceptable by an ergonomist. However, since these loading estimates were made based on incorrect data, situations could be labeled as unacceptable when they actually were not. The repercussions in a plant setting could be severe, as an entire job may be redesigned based on faulty recommendations.

2.4: Cumulative Loading:

Researchers in the biomechanics and ergonomics fields are becoming increasingly aware of cumulative loading as a factor linked to LBP development. The summation of forces at the lumbar spine over time has been found to be a good predictor of symptomatic osteochondrosis or spondylosis disorders of the lumbar spine (Seidler et al., 2001), as well as being linked to disc herniation during activities such as manual material handling (Seidler et al., 2003). Although past research efforts and lifting limits have focused primarily on peak loads (Waters et al., 1993), it is becoming apparent that jobs where workers don’t exceed NIOSH’s Action Limit of 3400 N of compression, are still becoming injured. When Punnett et al., (1991) examined automobile industry workers, they found that less than 3% of the examined postures yielded peak compressions as high as 3430 N, a value extremely close to NIOSH’s Action Limit, yet considerable low back pain was reported.

Cumulative loading on the low back has been shown to be a risk factor for LBP in more than one instance. For example, the load on the lumbar spine was documented during occupational manual materials handling tasks, including surface construction, metal processing, meat processing and refuse collection (Jager et al., 2000). Jager et al. (2000) discovered that, in comparison to recommended limits for maximal compression
from the literature, lumbar loads were exceeded many times over a shift. Jager et al. (2000) also proposed that force be weighted greater than exposure time when estimating cumulative exposures, including a tetra-powered function for force. Additionally, Norman et al. (1998) found significantly higher cumulative loading in automobile assembly plant workers who had reported pain in comparison to those who had not (Norman et al., 1998). Finally, Kumar (1990) showed that institutional aides with pain yielded higher cumulative compression and shear forces at the thoracolumbar and lumbosacral spinal level than those without pain.

Cumulative loading has been considered in the health care field, as well. Daynard et al., (2001) compared the effectiveness of two patient-handling techniques in minimizing injury risk. They found that subjects who did not use the patient-handling techniques experienced significantly higher peak loads in the spine than those who did. Additionally, Daynard et al. (2001) discovered that the use of assistive equipment increased the time requirements on certain patient-handling tasks than if the tasks were performed manually. This increase in exposure duration led to increased cumulative loading on the spine, drawing the conclusion that assistive devices for patient care are not always the ideal approach to injury risk reduction.

Using in-vitro methodologies, Hardy et al., (1958) performed repetitive loading on five spine specimens, each consisting of five lumbar vertebrae. Although annulus injury was not observed, compression fractures were present beginning after only 200 loading cycles which ranged from 0.5 to 4.5 kN of compression (Hardy et al., 1958). Other researchers have cyclically loaded vertebral segments to failure (Liu et al., 1983; Hansson et al., 1987). Liu et al. (1983) noted irreversible height loss in some vertebral
specimens which was taken as a sign of compression fracture, following loading between 60% and 80% of maximum compressive strength. These fractures occurred at load cycles less than 2000 (Liu et al., 1983). Hansson et al. (1987) found failure to occur between 1 and 1000 loading cycles following loading between 60% and 100% of maximum compressive strength.

Brinckmann et al. (1988) tested specimens consisting of vertebral segments that were subjected to cyclic axial compressive loading, meant to mimic the loading patterns that occur during lifting. All specimens decreased in disc height due to water loss and viscoelastic deformation, and fracture was also observed. Brinckmann et al. (1988) concluded that fatigue fractures like those observed in their study could contribute to the development of low back problems. Callaghan & McGill (2001), who examined intervertebral disc herniation, found that it may also be linked to repeated flexion/extension motions when young porcine specimens are tested.

Finally, Yingling et al. (1997) examined the effect of loading rate on cervical porcine specimens during compressive loading. They found that more dynamic loading (i.e. higher loading rates) increased the ultimate load applied in comparison to lower loading rates, and that this factor was more important than the magnitude of the dynamic loading itself (Yingling et al., 1997). Overall, such results indicate once again that it is perhaps the accumulation of sub-maximal loads over time that is causing much of the low back pain seen in industrial settings where peak loads are not excessive.

Some activities in the home have also been found to produce cumulative low back loads similar to those found in industry (Lauder et al., 2002; Lauder & Andrews, 2002; Azar et al., 2005). Godin et al., (2004) conducted a similar study with a 3-dimensional
rigid link segment model to determine cumulative outputs. Godin et al. (2004) found an estimated mean cumulative compressive load of 9.7 MN*s, demonstrating again that significant loads occur in the low back during non-occupational work. They also found that on average, subjects were in neutral trunk postures for 85.3% of the time, indicating that even though work in the home may not appear to be strenuous in terms of severe postures and heavy lifting, substantial low level loading is accumulating over time.
Chapter III - Methodology

3.1: Subjects:

Forty-five male and forty-five female subjects (n=90) were recruited to participate in the current study. All subjects were recruited from the University of Windsor's undergraduate and graduate programs. Subjects were initially divided into three groups based on their educational background, experience with, and knowledge of posture assessment methods. The 'Novice 1' group was comprised of undergraduate students who were currently enrolled in any program excluding Kinesiology (e.g. Business, Law, etc.). The 'Novice 2' group was comprised of undergraduate students who had completed an undergraduate course in functional human anatomy. These subjects were placed in this group based on the assumption that they would be more proficient at the task than the Novice 1 group, due to their increased familiarity with the human body. The 'Expert' group was comprised of undergraduate students who had completed undergraduate courses in ergonomics and human factors in addition to human anatomy, and graduate students who had completed a graduate ergonomics course, and/or had practical experience working with posture matching tools. These subjects were chosen to be in this group based on the assumption that they would be more proficient at the task than both of the Novice groups, due to their knowledge of and/or experience using posture matching tools. Please see Table 1 for subject anthropometrics.

Table 1: Subject Anthropometric Mean Values (SD)

<table>
<thead>
<tr>
<th>Anthropometric Measure/Expertise Group</th>
<th>Novice 1</th>
<th>Novice 2</th>
<th>Expert</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>F (n = 15)</td>
<td>M (n = 15)</td>
<td>F (n = 15)</td>
</tr>
<tr>
<td>Height (m)</td>
<td>1.5 (0.07)</td>
<td>1.7 (0.05)</td>
<td>1.6 (0.05)</td>
</tr>
<tr>
<td>Mass (Kg)</td>
<td>58.5 (6.6)</td>
<td>82.6 (13.9)</td>
<td>61.3 (6.2)</td>
</tr>
<tr>
<td>Age (yrs)</td>
<td>23 (2)</td>
<td>25 (2)</td>
<td>19 (1)</td>
</tr>
</tbody>
</table>
3.2: Apparatus

Data were collected using standard PC computers and monitors. The software used included ‘.jpeg’ images of people in various flexion/extension (49 images x 3 repetitions per image) and lateral bend (20 images x 3 repetitions per image) postures. These postures were chosen as they are common postures required to perform typical job tasks by workers in industrial settings. The clips appeared on the computer screen in random order, with all flexion/extension images grouped together, and all lateral bend images grouped together. The order of the flexion/extension and lateral bend images was counterbalanced across all subject groups. The software interface (Figure 2b) was similar to 3DMatch’s (Figure 2a) interface so that subjects were able to view the ‘.jpeg’ image while also viewing the posture bin options for either flexion/extension or lateral bend along the bottom of the screen.

The apparatus functioned as follows; subjects viewed the person in the given image, decided which bin the person’s posture fell into, and then clicked on the selected posture bin using the mouse. The program then cycled to the next image, and this same process was carried out for the remainder of the images. Subject data was automatically stored after every view trial.
Figure 2a: 3DMatch interface – example for flexion/extension

Figure 2b: Boundary Testing Program interface – example for flexion/extension

The software output displayed the person’s actual trunk angle on the video image (either trunk flexion/extension or lateral bend), the relative difference between the image and the nearest bin boundary, the correct posture bin, whether the selection made was correct or incorrect, and the chosen incorrect posture bin (if applicable). When a correct posture bin was selected (i.e. the subject selected the bin appropriately depicting the trunk...
posture on the image), a value of '1' was stored in the date file. If an incorrect posture bin was selected (i.e. the subject selected an inappropriate bin in comparison to the image’s actual posture), a value of '2' was output to file.

All images on the program interface consisted of trunk postures in 1 and 2 degree increments. Each flexion/extension bin was represented by a total of 14 images, 7 images on each side of the midline of the bin between the bin boundaries (Figure 3). Each flexion/extension posture image was presented 3 times in random order throughout the trial for each subject. As the data acquisition software interface was modeled after 3DMatch’s, the 3DMatch posture bins were employed in the software. The full range of 3DMatch’s flexion/extension postures are divided into 6 posture bins or categories. For the purposes of this study, only 4 bins were used with the assumption being made that no person would typically extend beyond -15 degrees or flex beyond 105 degrees, eliminating these bins. These extreme bins were therefore eliminated. Within the 4 tested flexion/extension bins, the boundaries that were considered were at -15, 15, 45, 75 and 105 degrees. Therefore, there were seven 14-degree ranges and 5 boundaries that were tested (Figure 3). For flexion/extension, the neutral positions were from -15 to 15 degrees, the moderate positions from 15 to 45 degrees, and the severe positions were greater than 45 degrees.
Figure 3: Flexion/extension 14-degree testing increments (Each arrow represents a 14-degree testing area to yield a total of 7 ranges. The arrows show in which direction that range exists, e.g. first arrow shows range existing between 0 and 15 degrees. For the flexion/extension category there are 7 14-degree testing ranges with a total of 5 bin boundaries.)

3DMatch lateral bend postures are divided into 3 bins to the left, and 3 bins to the right in the program. For the purposes of this study, only laterally bending to the left was shown, and the assumption was made that no person would typically laterally bend beyond 90 degrees, eliminating that boundary. This left 3 potential selection bins that were divided in half. Within these 3 bins, the boundaries that were considered were at 0, 15 and 30 degrees. However, the largest angle depicted in the lateral bend images was a lateral bend of 38 degrees, therefore, there were five 7-degree ranges and a final third
range greater than 30 degrees that were tested with 2 boundaries (Figure 4). For lateral bend, neutral positions were from 0 to 15 degrees, the moderate positions were from 15 to 30 degrees, and the severe positions were greater than 30 degrees.

![Diagram showing lateral bend testing increments](image)

**Figure 4:** Lateral bend 7-degree testing increments (Each arrow represents a 7-degree testing area to yield a total of 5 ranges. The arrows show in which direction that range exists, e.g. first arrow shows range existing between 1 and 7.5 degrees. For the lateral bend category there are 5 7-degree testing ranges with a total of 2 bin boundaries.)

3.3: Methods:

3.3.1: Experimental Design

Part I of this study was a 3x2x3x3 (Group x View x Repetition x Position) mixed design. Expertise group (Novice 1, Novice 2, Expert) was the between subject factor, and View (flexion/extension, lateral bend), Repetition (1st, 2nd, 3rd), and Position (neutral, moderate, severe) represented within subject factors (Table 2). The dependent variable in
Part I was the total error made by each subject. Absolute and relative errors were used for Hypothesis 1, and relative error only was used for Hypotheses 2-6. ‘Absolute’ error is the total number of errors made on average by a subject group (i.e. sum of total errors made by subjects in an expertise group divided by 30 subjects per group). Note that for Hypothesis 1, ‘relative’ error was calculated with respect to the total number of trials seen in each view (i.e. 147 for flexion/extension, and 60 for lateral bend). For Hypotheses 2 through 6, the ‘relative’ error was calculated with respect to the total number of options in each condition as specified by ‘view’ and ‘position’. Table 2 shows the mixed research design used for Part I of this study.

For Part II of this study, the dependent variables were peak and cumulative loads, (i.e. moments, and compression and shear forces at L4/L5). Although an ANOVA was not used, loading values were compared using gender, expertise group and scenario.

**Table 2**: Mixed 3x2x3x3 Research Design

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<tbody>
<tr>
<td>Group</td>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Novice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Flexion/Extension</td>
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<tr>
<td></td>
<td>Lateral Bend</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Novice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Flexion/Extension</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Lateral Bend</td>
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<tr>
<td>Expert</td>
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<tr>
<td></td>
<td>Flexion/Extension</td>
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<td></td>
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<tr>
<td></td>
<td>Lateral Bend</td>
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</tbody>
</table>
3.3.2: Data Collection

All subjects were required to sign a Consent Form approved by the Research Ethics Board at the University of Windsor prior to beginning their testing session. Normally, prior to analysis using 3DMatch, a user completes a training program to become familiar with making posture matching decisions. In the current study no such training program was implemented so as not to train those subjects who did not already have posture matching tool training/knowledge.

Computers located in the student computer lab on the 2nd floor of the Human Kinetics building at the University of Windsor were used for this study, and all subjects were instructed via e-mail to report here for their testing session. Novice 1, Novice 2, and Expert groups were divided; half of each group would view a person in flexion/extension trunk postures on the computer screen first followed by lateral bend postures, and the other half would view a person in lateral bend trunk postures first, followed by flexion/extension postures (see Table 2). Upon commencing the testing session, the investigator read instructions to the subjects on how to use the computer testing program. The investigator verbally walked subjects through logging into the program, and once this was complete subjects began the test. Identical instructions were given to every testing group.

Following instructions, subjects viewed a series of postures on the interface in either flexion/extension or lateral bend. Each subject viewed both flexion/extension and lateral bend images. The subjects were required to decide which of the given posture categories the subject’s trunk posture fit into, and then select this posture. They repeated this same process for all postures viewed in the testing session. Three trials per posture
image were completed, and subjects viewed 49 images in the flexion/extension view (total of 147 trials) and 20 images in the lateral bend view (total of 60 trials).

Once subjects had completed their first view trial (i.e. flexion/extension or lateral bend), they would raise their hand, and the investigator would help set them up for their next view trial using the same instructions used at the beginning of the session. When each subject had totally completed their testing session they were instructed to raise their hand again. The investigator confirmed that all of their selections had been saved to the hard drive of the computer, and then instructed the subject to logout of the program and exit the testing room quietly. The entire session took subjects approximately 30 minutes to complete.

3.3.3: Data Processing

For Part 1 of this study, the data processing was carried out as follows;

The collected data was processed by way of the data acquisition software itself and Microsoft Excel. The software showed error measures, such as the location of the errors made by each subject (i.e. in which bin), and the location of the correct bin, and these were exported into an Excel spreadsheet. The program outputs (i.e. number of errors as separated by degree location, group, view, repetitions and position) for each subject were compiled, and the data input into a statistics program (Statistica Version 5.1) for analysis.

For Part 2 of this study, the data processing was carried out as follows;

The second purpose of this study was to determine the effect the quantified bin misclassification error had on subsequent low back outputs. To determine this effect, two 3DMatch analyses were performed on several video clips showing a variety of activities
comprising different postural demands. Three different video clips (of approximately 1 minute in length or ~180 frames), each representing a different scenario were analyzed. The scenarios are described as follows:

- Scenario 1 - mostly neutral postures and no load being lifted.
- Scenario 2 - moderately flexed and laterally bent postures with medium loads being lifted (5 and 10 kg).
- Scenario 3 - more severe postures with a heavy load being lifted (20 kg).

The scenarios were chosen to show a variety of ranges of severity of posture and loads lifted, and to give a fair representation of the types of manual material handling tasks that occur in industry.

The correct analyses involved all posture category selections being correct. 3DMatch posture files were created for each of the three scenarios. A pre-determined list was used to represent each scenario, describing the bin selections that must be made. These selections were made in 3DMatch to create these posture files, and subject anthropometrics for each expertise group and gender were input (Table 1). The posture files were then used to create a total of 6 3DMatch model files; this was the ‘correct’ analysis.

The incorrect analyses involved some postures being purposely misclassified into incorrect bins. In Part I of this study, histograms were created to show which bins subjects made their errors in, and the relative error made in each bin (as a percentage of the total choices in that condition). As over 99% of all bin selections were made in the correct bin or adjacent bins to the correct bin, the adjacent bins were the only locations where misclassifications were made during the incorrect analyses. A master sheet was
made showing what percentage of bin selections resulted in error, expressed in terms of ‘group’, ‘view’, and ‘degree location’. The correct bin selections were then tabulated to determine how many images existed in each of the defined conditions (e.g. Novice 1, flexion/extension, 4 degrees away from the nearest boundary). Percentages from the histograms were then used to determine how many of these images would result in misclassifications either one bin greater than the correct bin, or one bin less than the correct bin. Once it had been determined how many errors must be made in each condition, the investigator randomly selected which images would be misclassified. New 3DMatch posture files were then created implementing these pre-determined errors, again using the anthropometrics for expertise group and gender mentioned above. These files were run through 3DMatch to yield 6 3DMatch model files; this was the ‘incorrect’ analysis.

3DMatch outputs from the correct analyses were then compared to the outputs from the analyses with the incorrect selections, and the differences in peak and cumulative loading estimates (including moments, and compression and shear forces at L4/L5) were compared.

3.3.4: Statistical Analysis

The statistical procedures for Part 1 of this study were as follows:

An ANOVA was used to determine if significant differences existed between the absolute and relative error made at each degree location. The dependent variables tested were absolute and relative error, and the independent variable tested was ‘degrees away from the boundary’. Alpha was set to 0.05 for these comparisons. This statistical procedure addressed Hypothesis 1. Additionally, a 3 x 2 x 3 x 3 (Group x View x
Repetition x Position) mixed ANOVA with repeated measures on View, Repetition and Position was conducted for relative error, and a Tukey HSD Post Hoc test was performed for significant main effects and interactions. The independent variables tested included ‘group’, ‘view’, ‘repetitions’ and ‘position’. Alpha was set to 0.05 for all such comparisons. This statistical procedure addressed Hypotheses 2-6. Omega squared values were calculated for significant interactions to determine if they contributed to more than 5% of the variance. All significant interactions were found to contribute to more than 5% of the overall variance, and were thus analyzed and discussed.

*The statistical procedures for Part 2 of this study were as follows;*

The relative difference between the peak and cumulative loads from the correct (no posture misclassifications made) and incorrect (posture misclassifications made) analyses was calculated using Equation 1.

\[
\text{% Difference} = \frac{\text{Correct} - \text{Incorrect}}{\text{Correct}} \times 100\%
\]  

[1]

This test determined if the ‘correct’ peak and/or cumulative load outputs were different from the ‘incorrect’ outputs.
Chapter IV - Results

Part I

4.1: Group and Degrees Away from Boundary:

There were significant main effects of ‘group’ and ‘degrees away from the boundary’ for absolute \( F(2, 87) = 7.78, (p<0.05); F(6, 522) = 76.95, (p<0.05) \) and relative \( F(2, 87) = 7.78, (p<0.05); F(6, 522) = 76.95, (p<0.05) \) errors, respectively, in the flexion/extension view (Figures 5, 6, 7 and 8). A significant main effect only was found for ‘degrees away from boundary’ in the lateral bend view, for both absolute \( F(3, 261) = 41.18, (p<0.05) \) and relative \( F(3, 261) = 41.18, (p<0.05) \) values (Figures 5, 6, 9 and 10). Both main effects will be later discussed as they were involved in a higher order interaction.

**Figure 5:** Mean Error by Group for both views. (Mean Error (i.e. total number of errors divided by 30 subjects per group) by Group for both views. Differences between groups were found to be significant for the flexion/extension view only (★ = p<0.05).)
Figure 6: Relative Error by Group for both views. (Relative Error (i.e. relative to total number of trials in each view: 147 Flexion/Extension and 60 Lateral Bend) by Group for both views. Differences between groups were found to be significant for the flexion/extension view only (★ = p<0.05).)

Figure 7: Mean # of Errors by Degree Location for all expertise groups (flexion/extension). (Mean # of Errors (i.e. total number of errors divided by 30 subjects per group) by Degree Location for all expertise groups. All levels of ‘degrees away from boundary’ were found to be significantly different from one another for the flexion/extension view (p<0.05).)
**Figure 8:** Relative Error by Degree Location for all expertise groups (flexion/extension). (Relative Error (i.e. relative to total number of trials in each condition, 21 at each degree location) by Degree Location for all expertise groups. All levels of ‘degrees away from boundary’ were found to be significantly different from one another for the flexion/extension view (p<0.05.).)

**Figure 9:** Mean # of Errors by Degree Location for all expertise groups (lateral bend). (Mean # of Errors (i.e. total number of errors divided by 30 subjects per group) by Degree Location for all expertise groups. All levels of ‘degrees away from boundary’ were found to be significantly different from one another for the lateral bend view (p<0.05.).)
**Figure 10:** Relative Error by Degree Location for all expertise groups (lateral bend). (Relative Error (i.e. relative to total number of trials in each condition, 15 at each degree location) by Degree Location for all expertise groups. All levels of ‘degrees away from boundary’ were found to be significantly different from one another for the lateral bend view (p<0.05).)

**4.2: Group x Degrees from Boundary Interaction:**

A significant interaction existed between ‘group’ and ‘degrees away from the boundary’ (p<0.05) for flexion/extension absolute errors \( F(12, 522) = 1.98, (p<0.05), w^2 = 0.019 \) and relative \( F(12, 522) = 1.98, (p<0.05), w^2 = 0.019 \) (Figures 7 and 8), as well as for lateral bend absolute \( F(6, 261) = 2.30, (p<0.05), w^2 = 0.05 \) and relative \( F(6, 261) = 2.30, (p<0.05), w^2 = 0.05 \) errors (Figures 9 and 10).

For the flexion/extension view, significant differences were found to exist between all degree locations except for between 10 and 12 degrees away from the boundary for the Novice 1 group (Figures 7 and 8). These results were paralleled for the Novice 2 and Expert groups, where significant differences were again found between all degree locations except between 10 and 12 degrees away from the boundary. The highest relative and absolute errors were found 2 degrees away from the nearest bin boundary.
over all expertise groups, and the lowest relative and absolute errors were found 14
degrees away from the nearest bin boundary (range from 4.8–9.8 errors (3.3–6.7%) from 2 to 14 degrees away from the boundary, respectively). The greatest decrease in error was found in the Expert group, followed by the Novice 1 group and then the Novice 2 group. For lateral bend, significant differences were also found to exist between all degree locations for the Novice 1 group (Figures 9 and 10). The Novice 2 and Expert groups displayed similar results, with significant differences being found between all degree locations. Additionally, the highest relative and absolute values were found 2 degrees away from the nearest bin boundary, and the lowest relative and absolute errors were found 7 degrees away from the nearest bin boundary for all expertise groups (range from 2.4–4.6 (4.1–7.7%) from 2 to 7 degrees away from the boundary, respectively). The greatest decrease in error was again found in the Expert group, followed by the Novice 1 group and then the Novice 2 group, depicting the same results found in the flexion/extension view.

4.3: Group, View, Repetitions and Position:

An ANOVA for Hypotheses 2, 3, 4 and 5 revealed main effects for ‘view’ 
\[ F(1, 87) = 14.79, (p<0.05) \] (Figure 11) and ‘position’ \[ F(2, 174) = 50.65, (p<0.05) \] (Figure 12) only (p<0.05), but not for ‘group’ or ‘repetitions’. However, since ‘repetitions’ was involved in 2 significant interactions, within-subject Coefficients of Variation (CVs = (s / μ)*100%) were calculated and then averaged by group to determine its importance in this task. For flexion/extension, Experts displayed the highest CV (~5.2%) and the Novice 2 group the lowest (~2.2%). In the lateral bend view, the Novice
2 group showed the highest CV between repetitions (~10.8%), and the Novice 1 group the lowest (~4.9%).

A Tukey Post Hoc Test revealed that for ‘view’, subjects made significantly less errors when viewing images in lateral bend than in flexion/extension. The test additionally revealed that images viewed in the neutral posture yielded significantly less errors than those viewed in moderate or severe postures. (Note: only relative errors were analyzed for Hypotheses 2 – 5, as shown relative to the total number of options in each view condition in each position. The levels for ‘group’ and ‘repetitions’ were equal (i.e. =3 for both variables). However, the levels for ‘view’ and ‘position’ were unequal, and were thus accounted for in the relative calculations. For example, 21 images were seen by subjects in the neutral position in the flexion/extension view; relative error scores were calculated as a percentage of 21 images.) All independent variables, including ‘group’, ‘view’, ‘repetitions’ and ‘position’ were involved in a significant 3-way interaction (p<0.05), and will be discussed later in detail.
Figure 11: Relative Error by View. (Relative Error (i.e. relative to total number of trials in each condition; 147 for flexion/extension, 60 for lateral bend) by View for all expertise groups. Subjects made significantly less errors in the lateral bend view (p<0.05).)

Figure 12: Relative Error by Position. (Relative Error (i.e. relative to total number of trials in each condition over both views; 45 in Neutral, 66 in Moderate, 96 in Severe) by Position. Subjects made less errors in the neutral position than in moderate or severe positions (★ = p<0.05).)
4.4: View x Repetitions Interaction:

The ‘view’ x ‘repetitions’ interaction was found to be a significant interaction \( F(2, 174) = 11.91, \ (p<0.05), \ w^2 = 0.26 \) (Figure 13). For flexion/extension (View 1 (V1)), significant differences existed between the 1st and 3rd repetitions (R1 and R3) with more errors made in the 3rd repetition. For lateral bend (View 2 (V2)), significant differences existed between the 1st and 2nd, as well as between the 1st and 3rd repetitions, with the 2nd and 3rd repetitions showing the highest relative error, respectively (R1 and R2, and R1 and R3, respectively).

![Repetitions x View Interaction](image)

**Figure 13:** Repetitions x View Interaction. (Differences between Rep 1 and Rep 3 were found to be significant in flexion/extension. Differences between Rep 1 and Rep 2, and Rep 1 and Rep 3, were found to be significant in lateral bend \( p<0.05 \).)

4.5: View x Position Interaction:

‘View’ x ‘position’ was found to be a significant interaction \( F(2, 174) = 11.52, \ (p<0.05), \ w^2 = 0.10 \). This relationship is depicted graphically later in a higher order interaction. For flexion/extension (V1), significant differences were found between all positions, including between neutral and moderate (P1 and P2), moderate and severe (P2
and P3), and neutral and severe (P1 and P3). The most relative error existed when images were viewed in the severe position. For lateral bend (V2), significant differences existed between all positions. However, the most relative error existed when images were viewed in the moderate position for the lateral bend view. This interaction is also incorporated into a 3-way interaction to be discussed later (Figure 15).

4.6: Repetitions x Position Interaction:

'Repetitions' x 'position' was found to be a significant interaction \[ F(4, 348) = 4.76, (p<0.05), \eta^2 = 0.021 \] (Figure 14). For neutral postures (P1), a significant difference was found between the 1st and 3rd repetition, with more errors being made during the 3rd repetition. For moderate postures (P2), no significant differences were found. Finally, for severe postures (P3), significant differences were found between the 1st and 2nd repetitions (R1 and R2), as well as between the 1st and 3rd repetitions (R1 and R3), with the highest relative error found during the 1st repetition in both cases.

![Graph: Repetitions x Position Interaction](image)

**Figure 14:** Repetitions x Position Interaction. (Differences between Rep 1 and Rep 3 were significant in neutral positions, and differences between Rep 1 and Rep 2, and Rep 1 and Rep 3, were significant in severe positions (p<0.05).)
4.7: Group x View x Position Interaction:

The ‘group’ x ‘view’ x ‘position’ interaction was also significant \[F(4, 174) = 3.10, (p<0.05), \omega^2 = 0.04\] (Figures 15 a - c). Several significant differences existed between groups, as split up by view and position. For flexion/extension, significant differences existed between Novice 2 and Expert groups in moderate (P2) and severe (P3) positions (Figures 15 b and c) (p<0.05). Additionally, for lateral bend, significant differences existed between Novice 1 and Expert groups in the neutral (P1) position (Figure 15a) (p<0.05).
Figures 15 a, b and c: Group x View x Position Interaction. (a) Neutral: Flexion/extension - no significant differences. Lateral bend - significant differences between Novice 1 and Expert groups (p<0.05); (b) Moderate: Flexion/extension - significant differences between Novice 2 and Expert groups (p<0.05). Lateral bend - no significant differences. (c) Severe: Flexion/extension - significant differences between Novice 2 and Expert groups (p<0.05). Lateral bend - no significant differences.)
4.8: Location of Errors:

Histograms of bin choices were developed to show the distribution of incorrect bin selections made relative to the correct bin. These were created for near and far degrees relative to the bin boundaries (i.e. 2 and 14 deg for flexion/extension and 2 and 7 deg for lateral bend). These two conditions were further divided into neutral, moderate and severe position categories of both flexion/extension, and lateral bend. The categories were defined as in Table 3;

Table 3: Degree Categories for Flexion/Extension and Lateral Bend Histograms (Note: For histogram analysis, the ‘severe’ position category only includes images in the 75-105 degree range, excluding the 45-75 degree range. This category was altered to only include the most severe postures shown in the flexion/extension view)

<table>
<thead>
<tr>
<th></th>
<th>Flexion/Extension</th>
<th>Lateral Bend</th>
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</thead>
<tbody>
<tr>
<td>Neutral</td>
<td>1 – 15 degrees</td>
<td>1 – 15 degrees</td>
</tr>
<tr>
<td>Moderate</td>
<td>15 – 45 degrees</td>
<td>15 – 30 degrees</td>
</tr>
<tr>
<td>Severe</td>
<td>75 – 105 degrees</td>
<td>&gt;30 degrees</td>
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Percentages were calculated to show the proportion of bin selections that were made in the correct and surrounding incorrect bins. These percentages were calculated relative to the number of choices a subject had in each particular condition. For example, in the flexion/extension severe category ranging from 75 to 105 degrees, with images 2 degrees away from the nearest boundary, a total of 6 images were seen by a subject; thus the total number of errors was calculated as a percentage of the total 6 images. This same method was implemented for all conditions.

When examining flexion/extension bin classifications of images 2 degrees away from the nearest boundary, the majority of selections were correct, with the highest mean
percentage of correct selections being made in the neutral category (Figures 16 a, b and c). Similarly, for images 14 degrees away from the nearest boundary, the highest average percentage of selections to be correct, were found in the neutral category (Figures 16 d, e and f). Overall, approximately 99% of bin selections were made either in the correct bin, or in the bins immediately adjacent to the correct bin, in both view conditions. Correct bin selection percentages ranged from 40.6% to 78.9% when the image viewed was 2 degrees away from the nearest bin boundary. Additionally, correct bin selection percentages ranged from 58.9% to 97.8% when the image viewed was 14 degrees away from the nearest bin boundary.

The lateral bend results paralleled those found in flexion/extension. For lateral bend bin classifications of images 2 degrees away from the nearest boundary, the majority of selections were correct, with the highest mean percentage of correct selections being made in the neutral category (Figures 17 a, b and c). Regarding images 7 degrees away from the nearest boundary, the highest mean percentage of selections were also correct, and found in the neutral category (Figures 17 d, e and f). In all cases, errors were mostly made in the bins immediately adjacent to the correct bin. Overall, approximately 99% of bin selections were made in the correct bin, or either one bin above or below the correct bin, in both view conditions. Correct bin selection percentages ranged from 56.7% to 82.2%, and from 71.1% to 95.6% when the images were viewed from 2 degrees and 7 degrees from the nearest bin boundary, respectively.
Figures 16 a – f: Flexion/Extension Histograms for bin choices. (Flexion/extension histograms showing; (a – c) 2 degrees away from the bin boundaries in neutral, moderate, and severe position categories, respectively. (d – f) 14 degrees away from the bin boundaries in neutral, moderate, and severe position categories, respectively.)
Figures 17 a - f: Lateral Bend Histograms for bin choices. (Lateral bend histograms showing; (a – c) 2 degrees away from the bin boundaries in neutral, moderate, and severe position categories, respectively. (d – f) 7 degrees away from the bin boundaries in neutral, moderate, and severe position categories, respectively.)
Part II

Part II of this study sought to determine the magnitude of any differences that existed in cumulative and peak low back load estimates as a result of analyses performed with all bin selections made correctly versus those performed with various bin misclassifications. The correctly performed analysis consisted of correct posture bin selections being made 100% of the time in 3DMatch, and the output model files displaying the ‘correct’ loading estimates. The incorrectly performed analyses consisted of incorrect bin selections being made based on results from Part I, and these 3DMatch outputs serving as the ‘incorrect’ loading estimates. Error data obtained from Part I based on ‘group’ and ‘degrees away from boundary’ was used to determine the percentage of bin misclassification errors that would be made to the correct posture bin. The analysis was further divided by view (i.e. separate analyses completed for flexion/extension and lateral bend), and gender (male and female inputs). Finally, 3DMatch requires additional inputs including height, body mass and age. For each gender in every expertise group, averages were taken of the subjects’ heights, body masses, and ages, and input into the program.

Overall, differences in cumulative and peak load outputs can be expected when bin misclassification errors are made. The magnitude of the relative difference between correct and incorrect outputs is dependent on the initial values. In the current study, the shear measures yielded very high percent differences, ranging up to infinity in some cases. This occurred when the initial value was close or equal to 0, and any deviation from the 0 value resulted in percent differences of extreme magnitude. When only considering those percent differences that were not extreme, as well as those where the
'correct' and 'incorrect' values both equaled 0, approximately 68% of differences were overestimated, 32% were underestimated, and the percent difference average was 13.5% (calculated using absolute values). Of these values, percent differences ranged from 0 to 73.2%.

All results from Part II can be found in Tables 4a and 4b. Originally, results were separated by gender. However, the female and male results were similar, and were subsequently collapsed.

**Cumulative Low Back Load Estimates:**

Overall, predicted maximum compressive strength for force weighting outputs did not change from the correct to the incorrect analyses. Compression and force weighted compression all yielded percent difference values of < 5% over all groups. Scenario 1 (neutral postures, no load lifted) yielded much higher percent difference values for joint anterior shear, joint posterior shear, and reaction anterior shear, with the largest difference being present for the joint shear forces (underestimations ranging from 5% – 910%). The assessment of many other cumulative loads resulted in no change relative to the correct analysis when the incorrect analyses were performed. Overall, no concrete trends were observed with respect to expertise group.

**Peak Output Estimates:**

Scenario 3 (severe postures, heavy loads lifted) yielded no percent difference for extension moment, whereas Scenario 1 (neutral postures, no loads lifted) yielded differences up to approximately 68% between correct and incorrect analyses outputs. For the right lateral bend moment, Scenario 3 results displayed no percent difference again,
and Scenario 1 showed approximately 50% difference from experts only. Right axial twist moment and left lateral reaction shear variables gave identical results.

Extremely larger percent differences for anterior and posterior bone-on-bone shear variables existed in Scenario 1 output estimates, with Scenario 3 actually showing 0% difference for anterior bone-on-bone shear only. A similar trend existed for anterior trunk reaction shear, where Scenario 3 displayed a difference of 0% between the correct and incorrect output estimates, and Scenario 1 showed approximately 73% difference from all expertise groups. The assessment of many other peak loads resulted in no change relative to the correct analysis when the incorrect analyses were performed. Overall, no concrete trends were observed with respect to expertise group.
Table 4a: Part II Results for Cumulative Variables:

Legend for Tables 4a & b: (0-10% ✗, 10-25% ✗, >25% ✗)

<table>
<thead>
<tr>
<th>Cumulative Variables</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N1</td>
<td>N2</td>
<td>E</td>
</tr>
<tr>
<td>Predicted Max. Comp. Strength for Force Weighting (N)</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compression (N*s)</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Force Weighted Compression (N*s)</td>
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<td>-</td>
</tr>
<tr>
<td>Joint Ant. Shear (N*s)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Joint Post. Shear (N*s)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Reaction Ant. Shear (N*s)</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Reaction Post. Shear (N*s)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Rxn Right M/L Shear (N*s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rxn Left M/L Shear (N*s)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Extension Moment(Nm*s)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flexion Moment(Nm*s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right Lat Bend Moment(Nm*s)</td>
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<td>+</td>
</tr>
<tr>
<td>Left Lat Bend Moment(Nm*s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left Ax Twist Moment(Nm*s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right Ax Twist Moment(Nm*s)</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

(Note: Negative values indicate that the incorrect load was greater in magnitude than the correct, and positive values indicate that the incorrect load was less in magnitude than the incorrect. The absence of a positive or negative value indicates that the incorrect load was unchanged in comparison to the correct load.)
Table 4b: Part II Results for Peak Variables:

<table>
<thead>
<tr>
<th>Peak Variables</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N1</td>
<td>N2</td>
<td>E</td>
</tr>
<tr>
<td>Extension Moment (N*m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexion Moment (N*m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left Lat Bend Moment (N*m)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Right Lat Bend Moment (N*m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left Ax Twist Moment (N*m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Right Ax Twist Moment (N*m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max BnB Comp (N)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Min BnB Comp (N)</td>
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</tr>
<tr>
<td>Anterior Trunk BnB Shear (N)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Posterior Trunk BnB Shear (N)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anterior Trunk RXn Shear (N)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Posterior Trunk RXn Shear (N)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Left Lateral RXn Shear (N)</td>
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<td></td>
</tr>
<tr>
<td>Right Lateral RXn Shear (N)</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

(Note: Negative values indicate that the incorrect load was greater in magnitude than the correct, and positive values indicate that the incorrect load was less in magnitude than the incorrect. The absence of a positive or negative value indicates that the incorrect load was unchanged in comparison to the correct load.)
Chapter V - Discussion

Part I

In general, subjects made more errors the closer the viewed image was to a bin boundary, for both flexion/extension and lateral bend views. Additionally, when examining the effects of several independent variables on relative error, significant effects were found for view and position. Subjects made more errors when viewing images in the flexion/extension view than when viewing images in the lateral bend view, and more in moderate and severe postures than in neutral postures. The magnitude of errors was highly variable among all subjects, but subjects’ overall were repeatable in their posture bin selections. It was also revealed that when subjects did make incorrect bin selections, they made these errors in bins immediately adjacent to the correct bin, in the vast majority of cases. On average, a 13.5% difference was found between peak and cumulative load estimates from the correct and incorrect analyses, excluding outliers.

5.1: Expertise Level Group and Degrees Away from Boundary:

Hypothesis 1: As the angle between the person’s actual posture on the image and a bin boundary decreases, the number of bin misclassifications (i.e. absolute and relative error) will increase

Hypothesis 1 is accepted for both absolute and relative error values. The first portion of this study looked at the number of degrees an image was away from a bin boundary, and its relationship to the errors made by subjects. This effect was expressed in terms of expertise level and degree location. For both views, subjects overall were found to make more errors when the image viewed was closer to a bin boundary and held true for both absolute and relative errors. This result was expected as it has been
previously shown that subjects are more prone to making errors the closer an image or stimulus resides to a known boundary. Nicholson et al. (1997) stated that a subject’s discrimination ability is fairly consistent over a normal range of stimuli, but tends to deteriorate at extremes, such as boundaries. Downing (1988) also demonstrated that subjects have a decreased detection sensitivity when 2 stimuli (such as a posture image and a bin boundary) are close together. These findings support the results found in the current study.

There was no significant main effect for group in lateral bending, although an effect did exist for the flexion/extension view. A significant difference between the performance of subjects from the three expertise groups, including Novice 1, Novice 2 and Experts, could be arguably expected. Novice 1 subjects might be expected to make the most number of errors since they had no academic or practical experience with posture matching tools. Novice 2 subjects might be expected to make an intermediate number of errors since they have had some academic introductory exposure to posture matching tools, but no practical experience. Finally, Expert subjects might be expected to make the least number of errors since they have had extensive academic, and/or practical laboratory experience with posture matching tools. However, main effects for ‘group’ were not found in both view conditions. It is possible that although the Novice 1 group had no experience with posture matching tools, they compensated for this deficit by taking extra care in making precise posture selections. The Novice 2 and Expert groups may have made more errors than expected because they paid less attention during the posture matching test due to overconfidence in their skills. Extending this latter theory, the decreased number of errors made by the Novice 1 group, and the increased
number of errors made by the Novice 2 and Expert groups would have resulted in smaller differences between the group error means and no significance. Although explanations exist for both scenarios described above, it is unclear why the flexion/extension view resulted in significant differences between groups and the lateral bend view did not. Further research is needed to investigate this issue, where flexion/extension and lateral bend views are specifically compared using the same number of posture images.

A similar effect was reported by Weir et al. (2005) who examined the ‘just noticeable differences’ (JND) of subjects in a posture discrimination task. The novice group with the lowest level of experience displayed the worst performance overall, with the intermediate and expert groups displaying increasingly better performances, respectively. The significant difference existed between the novice and expert groups. Weir et al. (2005) suggested that their novice group displayed the poorest performance since they had only taken one anatomy course and had never been exposed to posture assessment tools. The mean JNDs of the intermediate and expert groups were not significantly different from each other. The current study found Experts to have the least errors in both views. The Novice 1 subjects displayed fewer errors than the Novice 2 subjects in the flexion/extension view, where the Novice 2 subjects displayed less errors than the Novice 1 group in the lateral bend view. Overall, experts attained the lowest error scores, agreeing with the results of Weir et al (2005). However, both sets of results differ from Lowe’s (2004) findings, demonstrating that self-reported years of experience did not correlate with accurate estimates of posture. Perhaps more research is needed in this area, to either refute or confirm Lowe’s statement, as it was clearly different from results found in the aforementioned studies.
5.2: Group x Degrees away from Boundary Interaction:

There was a significant 'group' x 'degrees away from boundary' interaction (p<0.05), for relative and absolute variables in both views. For mean absolute and relative errors in the flexion/extension view, the Novice 1 and Novice 2 groups made the same percentage of errors at approximately 2 degrees away from the nearest bin boundary. Results were similar for mean absolute and relative lateral bend view values, depicting an interaction occurring at approximately 2 degrees away from the nearest bin boundary. All three expertise groups had the same errors at this point, as illustrated by the crossed lines in Figures 9 and 10.

It was expected that the number of errors would increase the closer images got to the bin boundaries. Although the different expertise groups were expected to perform at different levels of accuracy, all groups were expected to perform worse the closer an image was to a bin boundary. Since 2 degrees away from a boundary is the closest image location to a boundary studied here, it was anticipated that all groups would make the highest number of their errors close to this location, leading to the interaction.

For flexion/extension, only the Novice 1 and Novice 2 groups made the same percentage of errors at the 2 degree marker. For lateral bend, all expertise groups made the same percentage of errors at the 2 degree location, as well. Thus, Experts are capable of performing at a more accurate level than both Novice groups when viewing flexion/extension posture images only; this was not true for the lateral bend posture matching task.

Significant differences were found between all degree locations except for between 10 and 12 degrees for flexion/extension (relative and absolute), and between all
degree locations for lateral bend (relative and absolute). The highest error scores were found 2 degrees away from the nearest bin boundary for both views, and the lowest error scores were found 14 and 7 degrees away from the nearest flexion/extension and lateral bend bin boundaries, respectively.

It is plausible that significant differences would exist between all degree locations for both views. Based on Weir et al.’s study (2005), on average, the smallest JND a subject was capable of detecting was approximately 2 degrees. Almost all degree increments (excluding the lateral bend increment from 6 to 7 degrees away from the boundary) were separated by 2 degrees, implying that subjects may be capable of differentiating between all given images yielding significantly different results at all degree locations. Further, since Downing (1988) demonstrated that subjects tend to make more errors as the difference between two stimuli decreases, or the difference between an image and a boundary in the case of the current study, subjects were expected to make a proportional increase in errors the closer images got to a bin boundary. This is what was found in this study, as all but one degree increment resulted in significant differences in error, and the error increased proportionally overall from the furthest degree location to the closest degree location.

**5.3: Group, View, Repetitions and Position:**

Several independent variables were tested to determine their effect on the relative error made by subjects. The variables tested were ‘group’ (3 levels: Novice 1, Novice 2 and Expert), ‘view’ (2 levels: flexion/extension and lateral bend), ‘repetitions’ (3 levels first, second and third repetitions), and ‘position’ (3 levels: neutral, moderate and severe postures).
5.3.1: Group

Hypothesis 2: Novice 1 subjects will make a significantly higher number of bin misclassification errors compared to Novice 2 and Expert subjects.

- Hypothesis 2 is rejected, yet a trend was noted. There were no significant differences between the average relative errors made by each expertise group, when collapsed across all other factors. As mentioned previously, there are multiple explanations for the lack of a main effect for this variable, which will be later discussed for the ‘group’ x ‘view’ x ‘position’ interaction.

5.3.2: View

Hypothesis 3: Subjects viewing lateral bend postures will make more bin misclassification errors compared to those subjects viewing flexion/extension postures.

Hypothesis 3 is rejected, as a significantly greater number of errors occurred when subjects were judging images depicting a person in flexion/extension postures compared to lateral bend postures. Among other reasons that will be later discussed, this result is surprising as subjects viewed 147 trials in the flexion/extension view versus only 60 trials in the lateral bend view. The flexion/extension view allowed for more training (i.e. more practice at posture matching), and it would be assumed that more practice at a task would yield better performance; in this case, the opposite was true. However, the flexion/extension view results can be taken as a more stable estimate of a user’s performance at the task since more trials were performed. If this is true, then perhaps the lateral bend results would have yielded higher error scores had a higher number of trials existed. The need for this issue to be researched is later discussed in the ‘Future
Directions' section. 'View' was incorporated into higher order interactions that will be later discussed in detail.

5.3.3: Repetitions

Hypothesis 4: Experts will display less variability than the Novice 1 and Novice 2 groups over the 3 trials viewed of the same posture image.

Hypothesis 4 is rejected as no main effect existed for repetition. Hypothesis 4 predicted that Experts would display the least amount of variability between the 3 trials viewed per image since they had the most experience with and knowledge of posture matching tasks. It was additionally hypothesized that the Novice 1 and Novice 2 subjects would show the highest amount of variability since they had little or no experience with these types of tasks, and would hopefully make correct selections on the second or third trial of the image if their first selection had been incorrect. The absence of a significant main effect indicates that all subjects across all independent variables were not significantly variable in their responses. When subjects performed a manual video digitization task over several test days, Sullivan et al. (2002) stated that high intra-observer reliability was found. Additionally, no significant differences were found due to subject, day or trial, indicating that several subjects/users could perform the task over several test days or trials without confounding the results (Sullivan et al., 2002). A similar situation should be considered for the posture matching task utilized in the current study, as it will often take users several days to complete a 3DMatch analysis depending on the clip's complexity and length.

However, within-subject coefficients of variation were calculated and collapsed over expertise group, to demonstrate the variance existing between repetitions. The
results revealed that for flexion/extension, Expert's showed the highest variability between repetitions, and the Novice 2 group the lowest. For lateral bend, the Novice 2 group demonstrated the highest variability and the Novice 1 group the lowest. These results suggest that although ‘repetitions’ was not found to be significant, subjects still performed differently over the 3 repetitions viewed, as was also found in Sullivan et al.'s (2002) study. Overall, subjects displayed higher variability in the lateral bend view than in the flexion/extension view. ‘View’ x ‘repetitions’, as well as ‘repetitions’ x ‘position’ were both found to be significant interactions, that will be described later in detail.

5.3.4: Position

Hypothesis 5: Postures viewed which are severe (i.e. >45 degrees of flexion for flexion/extension, and >30 degrees of lateral bend) will elicit a higher number of bin misclassification errors, than those postures viewed which are neutral or moderate.

Hypothesis 5 is accepted, as a significant main effect was found for ‘position’. Images viewed in the neutral posture were found to yield significantly less errors than those viewed in moderate or severe postures. This prediction was based on the results of Weir et al. (2005). They found that subjects displayed a larger JND when viewing severe postures than when viewing neutral or moderate postures. The results of the current study confirm this result.

However, it must be determined how relevant it is in industry if posture matching tool users are making more bin misclassification errors when images viewed are in moderate or severe postures. In a plant setting where an ergonomist is present, it is unlikely that most job tasks will require a worker to position themselves in a severe posture (i.e. >45 degrees of flexion or >30 degrees of lateral bend). Although moderate
positions may be more common, most ergonomists strive to keep workers in a neutral back posture (i.e. limited bending in any direction) as often as possible. When moderate or severe postures are permitted, they are typically only allowed in low frequencies in an ergonomic-controlled plant. Thus, even if subjects are prone to making more errors when viewing people in moderate and severe positions, the overall impact on load estimates should be low, as the frequency of such postures in industry is expected to be low (if the facility in question has ergonomic support). ‘Position’ was also involved in higher order interactions that will be discussed later in detail.

5.4: View x Repetitions Interaction:

Significant differences were found to exist between the 1st and 3rd repetitions for flexion/extension with more errors made on the 3rd repetition. Although the argument could be made that a training effect occurred after viewing the exact same image three times, this effect is unlikely in this particular case. It is likely that three repetitions were not enough to yield a significant training effect, even if the three images were viewed in a row. Further, being that these three repetitions of the same posture image were viewed randomly throughout a series of 147 or 60 images for flexion/extension and lateral bend, respectively, it would be highly improbable that such an effect would occur over all subjects. However, subjects in general were eager to do well on this posture matching task and may have made more correct bin selections at the beginning of the task. As the task continued it is possible that some of the external factors proven to affect a subject’s ability to perform well (e.g. boredom, fatigue, etc.), began to take effect. These factors could cause subjects to make more careless errors in the latter phases of the session. The
relatively short overall time that all subjects took to complete the task contradicts this theory. More research is clearly required in order to test this in a controlled fashion.

Significant differences were revealed between the 1st and 2nd and the 1st and 3rd repetitions for the lateral bend view, with the 2nd and 3rd repetitions showing the highest relative error, respectively. The lateral bend view, however, only showed a difference between the 1st and 2nd repetitions. It is possible that subjects were extremely careful in making their posture bin selections closer to the beginning of the test (i.e. the first repetitions of each posture image), but became more careless as described earlier as the test progressed, leading to more incorrect responses and the 2nd and 3rd responses being significantly different from the 1st repetition.

Subjects may have made more errors when viewing flexion/extension postures for a variety of reasons. Firstly, flexion/extension postures occurred over a wider degree range than lateral bend postures (flexion/extension range from <-15 to >105 degrees in 6 potential bins, and lateral bend from 0 to >30 degrees in 3 potential bins). This wider range resulted in more degree locations where images were given to the subject for bin classification. More options may have increased the chance for confusion by subjects, and therefore caused them to make more errors while classifying postures. This is supported by the work of Lowe (2004) who showed that subjects performed better when they had fewer options to choose between, as was the case in the lateral bend condition. When less categories exist, there are less boundaries where a misclassification can occur.

Lowe (2004) also stated that a tradeoff exists between using more precise categories where a smaller likelihood of correct bin selections exists, and fewer categories where a higher likelihood of correct bin selections exists. In flexion/extension,
many more images (147) in more bins were viewed compared to in lateral bend (60 images).

Finally, the larger degree range in the flexion/extension view also meant that more severe postures were viewed in flexion/extension than in lateral bend (i.e. neutral postures made up 14%, moderate postures made up 29%, and severe postures made up 57% of the total number of images in the flexion/extension view). For lateral bend, neutral postures made up 40%, moderate postures made up 40%, and severe postures made up 20% of the total number of images. Subjects made more errors in this study when viewing severe postures in the flexion/extension view than neutral or moderate postures. This may help to explain why significantly more errors were made in the flexion/extension view than in the lateral bend view.

5.5: View x Position Interaction:

Significant differences were found to exist between all three positions, including mild, moderate and severe, for both flexion/extension and lateral bend views. The most relative error was found in the severe position for flexion/extension and in the moderate position for lateral bend.

It was hypothesized that severe postures would elicit the highest relative bin misclassification error, based on the results of Weir et al. (2005). They found that subjects had larger JNDS when viewing severe flexion/extension and lateral bend postures. This result signified that two postures must be further apart for subjects to perceive a difference between the two when the postures viewed were severe, implying that subjects would also be worse at classifying these postures.
Another possible explanation for this result is that subjects viewed more severe postures than any others for the flexion/extension view, which comprised a greater portion of the total number of images than in the lateral bend view. Although all error values were calculated relative to their respective condition (i.e. all percentages are relative to the number of images seen in each condition), the subjects viewed more overall images in the severe position. The higher number of choices leads to more opportunities for misclassification errors to be made, which may have influenced this effect (Lowe, 2004).

Subjects may also have more difficulty associating with and classifying severe postures compared to more neutral postures. The severe category in this study was >45 degrees for flexion/extension, and >30 degrees for lateral bend. To carry out regular activities of daily living and work, the average person is not usually required to position themselves in these postures. Godin et al. (2004) discovered that subjects maintained neutral trunk postures for approximately 85.3% of the time when household activities were being investigated. They additionally discovered that overall, little time was spent maintaining severe trunk postures (4.7% and 0.1% of subjects’ time was spent in severe flexion and severe lateral bend positions, respectively). Subjects may have more difficulty classifying a posture that they don’t regularly experience themselves. For example, if a subject is classifying a posture of a person flexing slightly at the trunk to pull clothes out of the washing machine, they may picture themselves doing the same task to estimate what their trunk posture would be. However, if the viewed image involves a person standing in a severely flexed posture that they themselves have limited experience with, it may be more unrealistic for them to classify this posture with accuracy.
Weir et al. (2005) also found that when postures were changing in the ascending direction, neutral and severe postures elicited greater JNDs from subjects than moderate postures. However, when postures changed in the descending direction, moderate and severe postures elicited greater JNDs from subjects than neutral postures, and the differences in this condition were of a larger magnitude. In both the ascending and descending directions, severe postures caused subjects to display a higher JND (i.e. less discrimination ability), implying that these postures are more problematic in posture discrimination or matching tasks.

5.6: Repetitions x Position Interaction:

For neutral postures, a significantly higher percentage of errors was made on the 3rd repetition than on the 1st repetition. No significant differences existed for moderate postures. For severe postures, a significantly higher percentage of errors was made on the 1st repetition than on the 2nd repetition and the 3rd repetition separately.

Regarding the result for neutral postures, the 3rd repetition could have yielded more errors due to the potential boredom or fatigue experienced by the subjects, as described earlier. Initially, the subjects were excited and energized to perform well on this task. However, as the test progressed, they may have become bored and began making either random careless choices, or simply poor choices due to their current state. A counterargument exists to explain the results found for severe postures. The 1st repetition could have yielded the most error as it was the first opportunity subjects had to view this posture image. However, as the posture image appeared for the 2nd and 3rd time, the subjects may have become more adept at the task, leading to a higher level of accuracy in making bin selections.
There is a slight possibility that subjects would have recognized the 2\textsuperscript{nd} and 3\textsuperscript{rd} repetitions as repeats of the initial image they had seen, and subsequently made the same choice they had on the 1\textsuperscript{st} repetition. However, with the person in the picture and the background being identical over every image viewed, combined with the images changing in 1 or 2 degree increments, it is next to impossible that subjects could have picked out the 2\textsuperscript{nd} and 3\textsuperscript{rd} repetitions of each image. Additionally, even if subjects were able to recognize the repeated images and made the same choice three times, there is no guarantee that their first choice was correct, and thus could not explain this interaction.

5.7: **Group x View x Position Interaction:**

Significant differences were found between Novice 2 and Expert groups in the moderate and severe positions for the flexion/extension view. For the lateral bend view, significant differences were found between Novice 1 and Expert groups in the neutral position.

The moderate and severe positions would have yielded significantly different percent error scores between Novice 2 and Expert groups because these postures were the most difficult to classify. Although the ‘group’ variable did not result in a significant main effect, Experts, Novice 1 and Novice 2 subjects made the most, intermediate, and least percentage of correct bin selections, respectively. The Novice 1 group may have exercised added care in making their posture bin selections knowing that they were the least experienced with posture matching, leading to a greater number of correct responses than expected. The Novice 2 group may have been overconfident in the amount of knowledge of and experience with such posture matching tools, thereby leading to a higher number of incorrect responses than expected. Overall, novices are not typically
expected to perform as well as experts. For example, novices are known to attend to
different attentional cues than experts who are already aware of what cues require
attention to perform a task well (Starkes & Allard, 1993). Additionally, novices do not
have an equivalent task-based memory to that of experts, also leaving them at a
disadvantage (Starkes & Allard, 1993). Novices experience perceptual limitations in
contrast to experts at a task, which allows experts to perform at a higher level (Saffel &
Matthews, 2003). However, novices have been shown to be trainable at perceptual tasks,
as well as being able to perform them at a higher level following training (Saffel &
Matthews, 2003; Goldstone, 1994). This implies that if trained, the Novice 1 and 2
groups could potentially narrow the performance gap between them and the Expert group.
Further research is required to determine if posture matching training would aid novices
in improving their performance.

The experts made the least number of errors, as expected. Experts at a task have
the ability to detect domain-specific stimuli that enables them to make more rapid and
more accurate responses in visual-cognitive tasks requiring discrimination (Clancy &
Hoyer, 1993). The current study demonstrated that experts do make more accurate
choices when faced with a posture matching task, and work is currently being done to
determine if experts do indeed make quicker responses, as well. The lack of a significant
main effect for group, however, could be explained by the fact that all experts had not
had practical experience with such tools (i.e. some had only extensive knowledge on
posture matching tools). This would have led to them making more errors than had been
predicted initially.
Since the moderate and severe postures are the most problematic to classify, it is logical that the worst and best performing expertise groups would show significantly different error scores. The experts had the background knowledge and past experience to draw on which allowed them to perform well even in the more difficult situations (Clancy & Hoyer, 1993), and the Novice 2 group simply did not have the equivalent background. Additionally, the flexion/extension view also yielded the most relative error in comparison to the lateral bend view over all expertise groups, again underscoring the larger difference in error between Novice 2 and Expert groups.

The neutral position may have resulted in significantly different error scores between Novice 1 and Expert groups because these are the two groups who are furthest apart in terms of experience with posture matching tools and the field of ergonomics as a whole. The moderate and severe positions were the most difficult to classify, challenging even the Expert group. The difficulty involved in classifying more severe postures brought the two groups’ error scores closer together. However, the neutral position was the easiest to classify and yielded significantly different responses between Experts and the Novice 1 group. This demonstrates the Experts’ skill at the task, and Novice 1 group’s inexperience, demonstrated by the Expert group’s significantly better performance.

5.8: Location of Errors:

Correct posture bin selections ranged from 54-84% in the flexion/extension view, and from 69-88% in the lateral bend view. In both cases, the lower end of the range was found when the image resided 2 degrees away from a boundary, and the high end of the range was found when the image resided 7 and 14 degrees away from a boundary for
lateral bend and flexion/extension, respectively. This finding signifies that all subject
groups, including the Novice 1 subjects who had no academic or practical experience
with observation-based posture matching tools or kinesiology as a field, were able to
make correct bin selections far more than half of the time. This gives a good indication
of 3DMatch's overall robustness, as even those subjects who have no experience at all
were able to make reasonably accurate selections without training.

The great majority of bin misclassifications were made in bins adjacent to the
correct bin (i.e. one bin greater or one bin less than the correct bin). In the majority of
cases, errors made one bin greater than the correct bin were made on images closer to that
high bin (relative to the midline), and those errors made one bin less than the correct bin
were made on images closer to that lower bin (relative to the midline). Additionally,
those errors that were made on images that were close to the middle of the bin (i.e.
around 14 degrees away from the nearest boundary in the flexion/extension view, and
around 7 degrees away from the nearest boundary in the lateral bend view), were
randomly distributed between those bins adjacent to the correct one. Subjects seldomly
selected bins that were not immediately adjacent to the correct bin. When they did it was
likely due to carelessness or lack of attention during bin selection. This result is
encouraging, as most misclassifications occurred in bins adjacent to the correct bin.

Part II

5.9: Cumulative and Peak Low Back Load Estimates from Correct and Incorrect
Analyses:

Part II of this study examined the magnitude of effect that the errors made in Part
I had on cumulative and peak loads from 3DMatch. Negative values indicate that the
incorrect load was greater in magnitude than the correct (i.e. incorrect load was an overestimate), and positive values indicate that the incorrect load was less in magnitude than the incorrect (i.e. incorrect load was an underestimate). Overall, Scenarios 1 (no load, neutral postures) and 2 (medium load, moderate postures) had the most overestimates, and Scenario 3 (high load, severe postures) yielded mainly underestimated loads. If the incorrect cumulative or peak load is larger than the correct load, the subjects overall were misclassifying bins by selecting bins adjacent to the correct bin. There were more overestimates across all scenarios, but the least number were present in Scenario 3.

In flexion/extension, bin misclassifications occurred one bin less than the correct bin with more regularity than one bin greater than the correct bin (i.e. 18 out of 21 bin conditions showed one bin down being chosen a higher percentage of the time than one bin up). A similar trend was found for lateral bend, with 10 out of 12 bin conditions showing one bin less than the correct bin being chosen more often than one bin greater than the correct bin. For flexion/extension, the only conditions where a greater bin was chosen more often than a lesser bin was from the Expert group. For lateral bend, however, the 2 conditions where the greater adjacent bin was chosen more often were from the Novice 1 group. The results suggest possibly that Experts tended to overestimate postural severity in flexion/extension more than other expertise groups, and that the Novice 1 group tended to overestimate postural severity in lateral bend more than other expertise groups. However, due to the limited number of conditions in which this trend existed, it is not sufficient to draw any definitive conclusions without further evaluation.
The overall results suggest that subjects tended to overestimate postures as opposed to underestimate them (68% versus 32%, respectively). This has several implications for posture matching tools such as 3DMatch. If this tool is being used in industry, and industrial ergonomists are basing critical decisions on outputs from such a program, then consistent overestimation of posture could lead to a job/condition being deemed ergonomically unacceptable when it actually is acceptable. In a work setting, overestimations lead to conservative decisions, such as a job being deemed unacceptable and potentially harmful to the worker, when in fact the job is not (i.e. a false positive). In such a situation, workers would be instructed by an ergonomist not to do as much physical work as they are actually capable of, potentially leading to increased manpower and/or decreased production. Although injury would most likely be decreased in such situations, a company as a whole could suffer production-wise if such decisions were made on a continual basis.

In some situations, the incorrect analyses resulted in loads dramatically larger in magnitude (i.e. percent difference approaching infinity) than those from the correct analysis. However, it is apparent that these situations occurred mainly with the shear variables, which had magnitudes of loading of 0 N initially. When the ‘incorrect’ analysis was performed, any error made in comparison to 0 would yield a large percent difference value. The average percent error overall (not including extreme values, or cases where ‘correct’ and ‘incorrect’ loading outputs were 0), was approximately 13.5%. This value is over all expertise groups, showing that even when the less accurate results from the novice groups were included, there were many more correct selections being made than incorrect ones. Despite this, it is also apparent from these results that although
subjects selected the correct bin more often than any other bin, that errors in
misclassification do translate into appreciable errors in low back loads.

It also needs to be considered how relevant these errors are to different industries,
and how significant errors of this magnitude could be on rating the acceptability of jobs.
For example, back injury claims have been found to be prevalent in the workplace
(WSIB, 2002). However, much of this injury data has come from professions such as
nursing, and not from industrial settings. More work must be done to tally low back
injury statistics over a variety of industries (e.g. automotive, poultry processing, mining,
tool and die, etc). Additionally, if low back pain is found to be predominant in such
industries, and on-site or contract ergonomists are present at these sites, further work
must be done to gauge whether the ergonomic changes being made to problematic jobs
are actually decreasing injury in these workplaces.

5.10: Limitations:

Regarding the testing program itself, the flexion/extension trial, comprising 147
images, was considerably longer than the lateral bend trial of 60 images. It is possible
that the length of the trials may have affected the results, as subjects had to spend more
time classifying flexion/extension postures than lateral bend postures. Future work
should determine if fatigue plays a role in error development using this approach.
Consideration will have to be given to the fact that anatomically, the range of motion for
lateral bend is much smaller than the range of motion for flexion/extension. This makes
it difficult to have an equal number of images in both views.

The use of graduate students in this study may have been a limitation, as they had
more knowledge of the purpose of the current study prior to testing. Whether this
knowledge gave them an advantage over other subjects is not clear from the results presented here. Future work should consider a tighter definition of ‘expert’. Salthouse (1991) defined an expert as possessing skills placing him/her in the highest percentiles of the normal distribution of skill in their task. In this study, this definition would identify ergonomists who are very proficient at using posture matching tools. The experts used in this study were definitely experts relative to the novice groups, but perhaps did not possess the same skill set inherent in field ergonomists who use these types of tools every day.

This study considered trunk flexion/extension and lateral bend postures only. The trunk was chosen due to the high prevalence of low back pain in the workplace today (WSIB, 2002). However, significant injuries do occur at the shoulder and elbow joints, as well, that also require attention. Additionally, due to how large the trunk segment is compared to the arm and forearm, it may be easier for users to respond with the correct bin selection. Previous research has shown that larger segments are more accurately classified during posture matching tasks than smaller ones (Li & Buckle, 1999; Lowe, 2004), implying that shoulder and elbow joint postures could be misclassified more than were found in the current study for the trunk. As a result, the effect of misclassification on the resultant joint loads at the shoulder and elbow is also unknown as a result of this work.

The Novice 1 group was comprised of subjects who had no prior academic involvement with the field of kinesiology as a whole. This group was included to gain a baseline perspective of how truly inexperienced and unknowledgeable users responded to the interface and task. The majority of subjects tested were in Business or Law programs
at the University of Windsor. It is unclear whether other non-Kinesiology students would have responded the same as those tested, but it is expected that course background might have an effect (e.g. an Engineering student might respond differently than a Sociology student due to the spatial nature of the assessment).

Due to the interface layout, the results from the computer program used in the current study are thought to be applicable to other similar posture matching tools, including 3DMatch, with several notable exceptions. The person that the subjects viewed in the images maintained the same body position with the exception of changing his trunk angle, and was always in front of the same backdrop. The person wore fitted pants and no shirt so that his trunk was clearly visible to the subjects, and faced forward for all flexion/extension postures and sideways for all lateral bend postures, to give subjects the optimal angle for easy viewing. When in industry, or in the home for example, full or baggy clothing and impaired camera views are common, as are changing or limited light conditions. These factors make classifying postures from in the field operations much more difficult in comparison to the images viewed in the program used in this study.

The speed/accuracy tradeoff may have also played a part in the results of the current study. It is possible that subjects just wanted to complete the test as quickly as possible, and sacrificed accuracy in bin classifications for speed. Further testing comparing time taken to make a decision and whether the decision was correct or not, will aid in clarifying this issue.

In Part II of this study, three loading scenarios were chosen which were representative of many different postures and loads that could exist in industry. Although a wide range of postures and loads were lifted, a posture image did not exist at every
single angle, and maximum load of 20 kg was lifted. Although the scenarios chosen were representative of a range of typical manual material handling tasks (with respect to posture and load), the range was limited.

5.11: Future Directions:

Future work is needed to examine other joints and the effect of bin misclassifications on peak and cumulative loads. For example, the role of additional training for operators needs to be assessed given that even Expert subjects made a fair number of errors in general in this study. The effect that improving the generalizability of the results has on errors also needs to be considered. Similar work done with practicing, experienced industrial ergonomists, and the use of images depicting a wide variety of non-laboratory environments should be studied to quantify their effect on error rates using the same interface. The experts used in the current study may have been experts in comparison to the novice subjects, but would not be considered experts when compared to field ergonomists who have been practicing for many years. For this reason, is it not surprising that the ‘group’ variable resulted in a lack of main effect, as the ‘expert’ group employed was probably closer in expertise level to the novices than an active ergonomist would be. In future studies, subjects could be put through a training module first, and then divided into expertise groups based on their performance on the specific task at hand. This may give a more accurate representation of which subjects are more proficient at a task, than making assumptions based on education level and laboratory experience.

Based on the results obtained in Part II of the current study, it is apparent that the bin misclassification errors being made are leading to inaccurate low back loads.
Decisions must be made on how these errors are going to be decreased to yield the most accurate outputs possible. Potential actions include decreasing the number of bins, and thus decreasing the number of comparisons that must be made by subjects and the potential for error. However, a tradeoff exists which will lead to less precise results with a decreased number of bins (Lowe, 2004). Studies should be conducted with a decreased number of bins, and results compared to those using the current number of bins to determine if accuracy is decreased, and if so by what magnitude.

Finally, further testing is required to compare flexion/extension to lateral bend, and neutral to moderate and severe postures. The focus of this work should be to determine why subjects have more difficulty classifying flexion/extension and severe postures. Controlling the number of images viewed in the conditions is an important consideration for this work.

This study was intended to increase the knowledge base of posture matching tools, and build on other related studies, such as the initial validation tests for 3DMatch by Callaghan et al. (2003), and the JND study by Weir et al. (2005), which investigated user perception by gauging subjects’ abilities to discriminate between 2 postures. The current study determined that subjects do make more bin misclassification errors the closer a viewed image resides to a posture bin boundary, irrespective of expertise level at posture matching tasks. However, it was also found that, excluding outliers, subjects’ overall misclassification error was only 13.5%, which is encouraging as even subjects with no prior experience with posture matching tools can perform at this level.
Chapter VI - Conclusions

This study was conducted to quantify the bin misclassification errors made by subjects based on several factors, including proximity to a bin boundary, expertise level, view, number of repetitions, and position. The effect that these misclassification errors had on cumulative and peak loads was then assessed. Based on the derived results, the following conclusions can be made:

- All subjects, regardless of expertise level, make bin misclassification errors.
- Overall, subjects make more errors the closer a viewed posture image resides to a bin boundary (3.3 vs. 6.7% error for 2 vs. 14 degrees away for flexion/extension, and 4.1 vs. 7.7% error for 2 vs. 7 degrees away for lateral bend).
- The flexion/extension view and severe postures were found to elicit more bin misclassification errors compared to lateral bend and the neutral and moderate posture categories.
- Bin misclassifications were found to occur in bins immediately adjacent to the correct bin the majority (>99%) of the time.
- Bin misclassification errors led to errors in peak and cumulative load estimates that ranged from small to large. Percent error on average when outliers were not considered was approximately 13.5%.
- Although no main effect was found for ‘group’, the Expert group yielded the least amount of errors in both the flexion/extension and lateral bend views, in comparison to the Novice 1 and Novice 2 groups.
References


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Vita Auctoris

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