Assessing the Utility of a Video-Based Motion Capture Alternative in the Assessment of Lumbar Spine Planar Angular Joint Kinematics

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ABSTRACT

Markerless motion capture is a novel technique to measure human movement kinematics. The purpose of this research is to evaluate the markerless algorithm, DeepLabCut (DLC) against a 3D motion capture system (Vicon Motion Systems Ltd., Oxford, UK) in the analysis of planar spine and elbow flexion-extension movement. Data were acquired concurrently from DLC and Vicon for all movements. A novel DLC model was trained using data derived from a subset of participants (training group). Accuracy and precision were assessed from data derived from the training group as well as in a new set of participants (testing group). Two-way SPM ANOVAs were used to detect significant differences between the training vs. testing sets, capture methods (Vicon vs. DLC), as well as potential higher order interaction effect between these independent variables in the estimation of flexion extension angles and variability. No significant differences were observed in any planar angles, nor were any higher order interactions observed between each motion capture modality and the training vs. testing datasets. Bland Altman plots were also generated to depict the mean bias and level of agreement between DLC and Vicon for both training, and testing datasets. Supplemental analyses, suggest that these results are partially affected by the alignment of each participant's body segments with respect to each planar reference frame. This research suggests that DLC-derived planar kinematics of both the elbow and lumbar spine are of acceptable accuracy and precision when compared to conventional laboratory gold-standards (Vicon).

ACKNOWLEDGEMENTS

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CHAPTER I: INTRODUCTION

1.1 Rationale for Research

Low back pain (LBP) is a common disorder that presents a significant and common socioeconomic burden on developed countries (Balagué et al. 2012; Williams et al 2015). Due to its ambiguous nature, it can be difficult to pinpoint the pathoanatomical cause of LBP (Hoogendoorn et al 2008). To accommodate the variability in the development and presentation of the disorder, LBP is often explained using the biopsychosocial model (Freeman et al. 1998). This model describes the complex integration of mechanical, psychological, and social factors in the development and progression of LBP. To address the multidimensional nature of low back disorders (LBDs), and to aid in the diagnosis, treatment, and rehabilitation of LBDs, past research has aimed to pinpoint the causes of LBDs through different quantitative measures (Gatton & Pearcy 1999; McGill, Grenier, Kavcic & Cholewiki 2003; Colloca & Hinrichs 2005). One common element to many of these measures is the acquisition of spine movement kinematics to infer relevant spine motor control parameters (Hodges et al., 2019). In many cases, standardized movement tests can be done to assess lumbar movement (Gatton & Pearcy 1999; McGill, Grenier, Kavcic & Cholewiki 2003), including the potential association between lumbar spine motor control, the presentation and development of LBP (O'Sullivan 2005). These objective assessments of spine movement are particularly useful in the development of an individualized approach in the management of LBDs, especially as previous studies have also shown that flexion of the spine is not uniform in all people (Gatton & Pearcy 1999; Beaudette et al., 2019). Traditionally, lab-based methods to measure spinal movement are typically very expensive and invasive with markers or sensors affixed to the skin. Further, these highly technical systems require in-depth technical knowledge to operate the machinery and software. Recently, machine learning and automated intelligence advancements have facilitated the development of new motion capture alternatives which aim to address many of the concerns noted above.

Novel, automated computer-vision based algorithms are now capable of tracking discrete body landmarks from an input video. Specifically, these products are capable of mapping and tracking many body parts without the use of markers or sensors affixed to the body being tracked (Insafutdinov et al. 2016). In large part, these novel models have been used to track the motion of the upper and lower extremities (Nakano et al., 2020; McKinnon et al., 2019), based on a set of trained landmarks; however, given the relative size and anatomical complexity of the spinal column (compared to the extremities) their utility in the assessment of spinal motion is currently unknown. This is largely due to the absence of common anatomical features which an automated algorithm may be able to evaluate to infer gross (i.e., lumbar, or thoracic) or multi-segmented movement. This neglected spinal motion could be monitored with specialized software that maintains the accuracy and precision of a traditional system with the functionality and non-invasive qualities of a markerless system (Insafutdinov et al., 2016). If a valid markerless motion capture alternative exists in the assessment of spine kinematics, this technology may be used to provide information on how the spine moves without the required domain knowledge, excessive cost, portability constraints that exist with common modern laboratory-based 3D motion capture systems. These systems could therefore add substantial versatility to biomechanical lab and field work, particularly in the clinical assessment of spine movement to aid in the potential diagnosis, treatment, and rehabilitation tracking of LBDs.

1.2 Summary of Previous Work

Previously, many motion analysis technologies have been effective in the tracking of spine kinematics in a laboratory setting. In the context of systems that measure the spine; optoelectronic, electromagnetic, and inertial systems are the most popular when collecting spinal movement data (Ferrario et al., 2002; Bolink et al., 2016, do Carmo & Vilas Boas, 2019 & Ceseracciu 2014). Many of these approaches require the tracking of markers or sensors affixed to the body of the participant, and although these kinematic systems are relatively non-invasive, they to present with a variety of limitations and constraints. For example, many systems lose their practicality and accuracy when removed from the lab setting due to environmental factors such as infrared radiation or ferromagnetic interference. Modern, video-based markerless approaches may afford a new alternative motion capture approach whish is less sensitive to these types of limitations and or constraints. Not only do these algorithms not require any wearable equipment such as markers or sensors, but they also have the additional benefit of being more portable, cost effective and require less domain knowledge (Kaimakis & Lasenby, 2004; Lucchetti et al., 1998).

Computer vision-based motion analysis involves extracting information from sequential images in order to describe movement. Historically, 2D motion capture data could be obtained from time-varying images (i.e., video) through the human-based labelling of relevant markers or structures on each acquired image. However, the recent rapid development of modern computer vision algorithms have improved the robustness, flexibility, and accuracy of markerless motion capture systems, which has spurred a rapid increase in interest within the biomechanics community. In general, a markerless motion capture solution has four major components: (1) the camera systems that are used, (2) the representation of the human body (the body model), (3) the image features used, and (4) the algorithms used to determine the parameters (i.e., pose, location) of the body model (Colyer et al., 2018). Typically, computer vision algorithms are trained offline, using input data from an acquired set of images to extract relevant outcomes of body segment location, pose, and shape. Using large publicly available, labelled datasets (i.e., ImageNet), these approaches have resulted in the development of computer-vision algorithms which are trained to models (i.e., DeeperCut) that can evaluate common body landmarks which are easy to visualize, and useful in the representation of whole-body multi-segment models across a large potential number of tracked human participants (Insafutdinov et al., 2016). The only large drawback in models such as these is their limited utility in the evaluation of novel structures/landmarks stemming from input data that these algorithms have not been trained to evaluate (i.e., anatomical landmarks for specific experiments, or those located on different anatomical regions, such as the spinal column).

Recently a software called DLC has been developed using principles of transfer learning. This approach allows a model previously built for one task (i.e., DeeperCut) to be used as the starting point for a model to accomplish a new task (i.e., the tracking of a novel marker set trained on a smaller dataset of different input images). Conventionally DLC implements DeeperCut as a starting point and uses other open-source computer-vision architectures (e.g., ResNet, MobileNet) to adapt the model for different use cases. This particular software was designed for adaptive motor control research across a range of model species (Nath et al. 2018; Mathis et al., 2019). It has been compared to other systems in terms of small-scale animal models. Human research has been used to validate DLC against clinical norms (Williams et al. 2020; Labuguen et al., 2019). In general, the advent of transfer learning approaches such as DLC have afforded researchers the flexibility to evaluate species and/or anatomical structures which have not been assess previously, with relatively little user input (Nath et al., 2018). As such, these models may be used in the assessment of outcomes related to spine motor control, without the need for specialized lab equipment and or expertise. Despite this, little previous work has been done to compare the abilities of DLC to traditional gold standard motion capture systems in humans. This is especially true for analysis of anatomically complex joints such as the lumbar spine. No studies have validated DLC to concurrently measure planar angles of spine flexion in healthy human subjects. Some research has validated markerless motion capture systems against simulated joint models (Schmitz et al., 2014) and clinical measures (Williams et al., 2020). However, no researchers have shown success in concurrently validating a markerless motion capture alternative against a conventional gold-standard alternative in the assessment of thoracolumbar spine movement.

1.3 Research Objectives

1.1.1 Purpose Statement

The potential utility of novel transfer learning-based computer vision algorithms (e.g., DLC) in the assessment of custom body landmarks would afford the necessary flexibility to accommodate a variety of potential research designs. If these novel algorithms are applied to analyze the motion of the spine, this technology can be used to help researchers understand the impact LBP has on spinal movement. By comparing this novel DLC approach to a traditional optoelectronic system, researchers will have the ability to understand the reliability functionality of this markerless system in the context of tracking 2D spinal movements (i.e., flexion-extension) relative to accepted laboratory gold-standards. This will facilitate the use of DLC to potentially become a surrogate for gold standard systems when measuring flexion of the spine, particularly in ecologically relevant scenarios when lab-based motion capture approaches are not a viable option. Therefore, the **purpose** of the current study was to compare planar time-varying angles of the lumbar spine (complex multidimensional joint) and elbow (simple hinge joint) derived from DLC, relative to those derived from gold-standard retroreflective kinematic systems (i.e., Vicon). Specific outcomes will include the assessment of relative accuracy and precision of DLC-derived planar kinematics relative to those derived from a gold-standard (i.e., Vicon). These data will determine whether tracking with DLC is a good surrogate for spinal flexion analysis.

1.1.2 Hypothesis Statement

We **hypothesize** that DLC will be effective at tracking planar angles of both the lumbar spine and elbow relative to gold-standard alternatives (i.e., Vicon). Due to the anatomical complexity of the lumbar spine relative to the elbow, we hypothesize that any error, potentially associated with out of plane movement, will be minimized for the elbow relative to the gross movement of the lumbar spine. Further, we expect that any outcome parameters related to joint angular displacement or angular displacement variability (i.e., precision) will not differ when compared statistically between DLC and Vicon. In general, we expect that the accuracy and precision of DLC will be within five degrees of error, an acceptable level of accuracy for most motor control-based assessments (Schmitz et al., 2015).

CHAPTER II: LITERATURE REVIEW

2.1 Spine Motor Control & Low Back Pain

2.1.1 Lumbar Musculoskeletal Anatomy and Motor Control

The spine is an anatomically complex series of interconnected irregular bones called vertebrae. Each of these bones are separated by an intervertebral joint (IVJ) which facilitates linear and angular movement along and about three principle axes. Generally, rotations about the mediolateral (ML) axis correspond to spine flexion-extension (FE) rotations about the anterior-posterior (AP) axis correspond to leftward and rightward lateral bending (LB) and rotations about the superior-inferior (SI) axis correspond to leftward and rightward axial twisting (AT). Collectively the capacity for 3D translations and 3D rotations at each IVJ afford six mechanical degrees of freedom (DoF) at each IVJ. With 23 IVJ contained within the human cervical, thoracic and lumbar spines (Park et al 2001; Panjabi 1992), this affords an incredible capacity for movement with 138 mechanical DoF along each IVJ from C2-S1. This large capacity for movement, and potential instability, requires a refined and adaptable motor control system. As described by Panjabi (1992) this stabilizing neuromuscular control system includes passive, active and neural subsystems which must work collectively to coordinate dynamic spine movement and to ensure spinal stability. The passive subsystem includes spinal ligaments and other tissues which are not under active control from the central nervous system (CNS). Typically, the tissues that make up this system are passive, as they do not provide resistive forces to spinal movement when the spine is in a neutral position (Ward et al., 2009). The ligaments in this system begin to produce reactive forces against movement at the end ranges of motion (Panjabi 1992). The active subsystem includes muscles and tendons that contribute to force generation about the spine. These tissues are under active control from the CNS and may generate tensile forces across a wide range of spine postures. The neural control subsystem includes multiple spinal and cortical circuits which are used to regulate muscle tension, and spine stiffness in order to maintain spinal stability. This stability is determined by the posture of the spine, including the balance of any internal/external loads and moments about the spine (Panjabi, 1992).

In a mechanical sense, the musculature and ligaments surrounding the spinal column are important in stiffening the position of the vertebrae as well as ensuring mobility about each IVJ. The spine stiffness generated from these passive and active tissues facilitate mobility and stability of the trunk during movement. Spine stability is ensured through the resulting spine stiffness generated by muscles and ligaments as they apply counteracting agonist and antagonist forces to the vertebral column (Gardner-Morse, Stokes & Laible 1995). For example, the resulting stiffness produced by muscle coactivation will prevent unwanted vertebral rotation and translation during movement (McGill, Grenier, Kavcic & Cholewiki, 2003). These passive and active stabilizing forces are especially important considering that an osteoligamentous spine, devoid of muscles and ligaments, will buckle under approximately 80-90 N of compressive load (Crisco et al. 1992). To compliment the mechanical systems noted above, the neural control subsystem uses spinal and cortical mechanisms to control the movement of the spinal column. Specifically, this system integrates afferent (sensory feedback) and efferent (muscular activation) information and accounts for the current state of the spine system, the planned movement being executed and passive/active tissue properties (Reeves et al., 2007; Hodges, 2011).

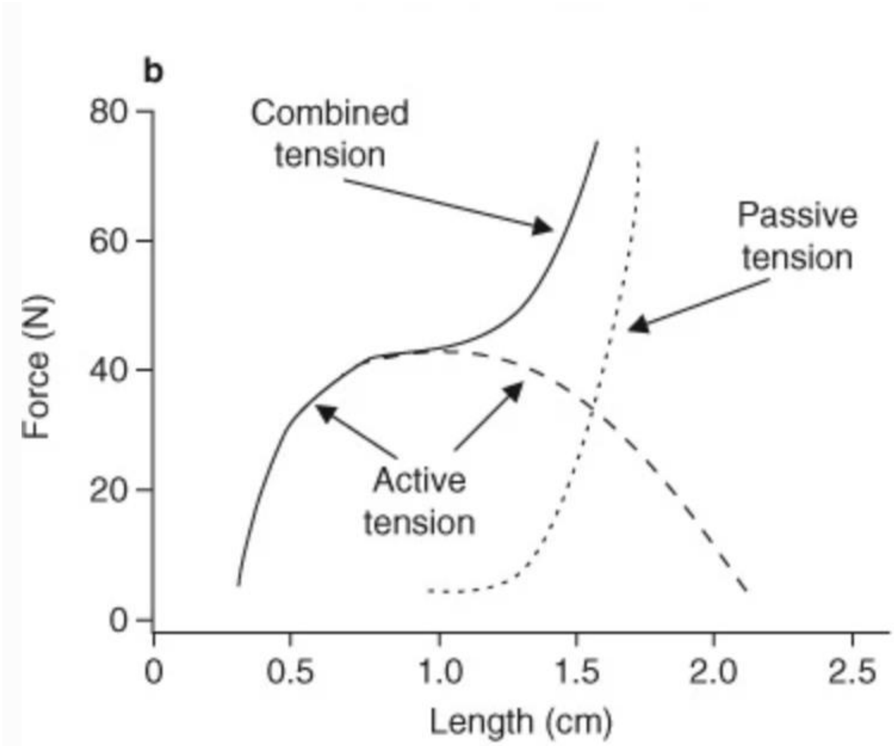

Figure 1: Length tension relationship demonstrating the force generation capacity of active and passive tissues at different lengths. Of note are the optimal force generating capacity of active tissues at moderate lengths (neutral postures) and the contribution of passive tension during lengths (postures) approaching end range-of-motion. Extracted from: Ward, S. R., Kim, C. W., Eng, C. M., Gottschalk IV, L. J., Tomiya, A., Garfin, S. R., & Lieber, R. L. (2009). Architectural analysis and intraoperative measurements demonstrate the unique design of the multifidus muscle for lumbar spine stability. *The Journal of bone and joint surgery 91*(1), 176.

2.1.2 Low Back Pain (LBP)

LBP is a common condition presenting a significant socioeconomic burden for industrialized countries (Williams et al 2015). Previous research has determined that 84% of the population experiences LBP at some point in their lifetime (Balagué et al. 2012). The pathology behind low back pain is often misunderstood and difficult to pinpoint. This is because the underlying cause of LBP may not be a result of mechanical illness, injury, or age. Psychological distress, psychiatric disorders and potential neurological disorders may also contribute to the pathoeitology of LBP (Andersson, 1999). The multiple factors which may contribute to this LBP are described by the biopsychosocial model (Freeman et al., 1998; Gianola et al., 2018). This model describes the complex integration of mechanical, psychological, and social factors in the development and progression of LBP. Due to this complicated and varying pathology, LBP has become one of the largest issues for the western continents public health system (Balagué et al., 2012). Nonspecific low back pain (NS-LBP) is defined by the symptoms of LBP without an identifiable physical pathology (Balagué et al., 2012). Factors that are deemed to be biomechanical or pathoanatomical may play a role in the LBP of a particular individual. For example, activities such as occupational lifting resulting in spinal flexion and rotation are moderate risk factors which can lead to LBP (Hoogendoorn et al., 2008). This discomfort due to LBP can considerably decrease the quality of life for those affected (Horng, Liang & Wang, 2005), particularly for those with long-term (i.e., chronic disorders). Patients who experience LBP chronically may also negatively adapt to sustained LBP. This negative adaptation is achieved through fear or pain avoidance strategies, often resulting in the fear of particular movements (i.e., kinesiophobia). These strategies are based on an emotional response of self preservation (Rainville et al. 2011). Once those experiencing LBP utilize the avoidance strategy beyond the expected time to heal, they may also resort to a disuse strategy. This means the individual experiencing pain decreases their levels of physical activity (Bousema et al., 2007). This lack of activity leads to deconditioning, which has been known to make the return to activity more difficult for the patient (Vlaeyen et al., 1995). Previously, a large volume of research has aimed to quantify how deficits in passive, active and neural spine motor control systems may contribute to the development and onset of LBP. Specific variables which have been investigated include the relative coordination of lumbopelvic movement (Gatton & Pearcy

1999; McGill, Grenier & Cholewiki, 2003), lumbar proprioception (Tong et al. 2017), spine stability (McGill, Grenier & Cholewiki, 2003) and the flexion relaxation phenomenon (Colloca & Hinrichs, 2005). Recently, many researchers have begun to suggest that person-specific motor control variables may have utility in the clinical assessment of spine function (van Dieën, 2019). Specifically, these variables may have clinical utility in the development of personalized care plans for those experiencing LBP. This is important as person specific motor control impairments can occur in the presence of LBP (O'Sullivan, 2005). Therefore, an important consideration is how typical biomechanical variables (i.e., spine movement kinematics) can be captured in a clinical environment.

2.1.3 Lumbar Spine Movement & Estimation of 3D Rotational Kinematics

Within a laboratory environment, spine kinematics have consistently been evaluated to indicate differences in the motor control strategies utilized by participants experiencing LBP relative to those who are pain free (e.g., Gomez, 1994: O'Sullivan. 2005). Due to the large prevalence of pain within the lumbar region (Hartvigsen, Natvig & Ferreira, 2013), much of the previous research has focused on the 3D assessment of movement (i.e., within the sagittal, frontal, and transverse planes) within this region. This information is used to understand differences in 3D motor control strategies used in healthy participants, and in those experiencing LBP. According to Laird et al. (2014), when comparing those with and without LBP, there were differences with movement across multiple categories. This includes, lumbar lordosis, ROM, lumbar spine versus hip contribution to flexion/extension, pelvic tilt angle, speed/acceleration of lumbar flexion and proprioception. The following paragraphs summarize some key findings from this recent systematic review (Laird et al., 2014).

Common postural measurements used throughout the literature include lumbar lordosis and absolute pelvic tilt. Lordosis angles are typically estimated by taking the relative angle between the T12 and S1 vertebrae within the sagittal plane. When comparing three studies (Christie et al., 1995; Day et al., 1984; Youdas et al., 2000; Youdas et al., 1996) lumbar lordosis did not display a significant difference between subjects with and without LBP. Pelvic tilt angles are taken by estimating the absolute angle of the pelvis during a standing posture. Similarly, the analysis of pelvic tilt angles do not achieve a consensus when comparing reports throughout the literature. Although, there were small consistent anterior pelvic tilt with those experiencing LBP relative to those without any apparent disorder. One study by Day et al. (1984) found a significant difference when comparing those with and without LBP when comparing maximum pelvic tilt values.

To understand the capacity for dynamic movement, spine ROM is typically evaluated by taking the difference in spine relative posture during two time points (e.g., neutral standing and full flexion). Spine movement ROM was the most common outcome measure reported in the comparison of LBP vs healthy participants. Typical average flexion ROM values are ~58.3 degrees when starting in a standing position or ~27.6 degrees when starting from a seated position (Gatton & Pearcy, 1999). Specifically, ROM proved to show differences between those with and without LBP in 26 studies as reviewed by Laird 2014, where those with LBP showed a reduction in ROM. In some cases, the relative contribution of spine and hip movement have been quantified in the coordination of a forward flexion movement. For lumbar vs. hip contribution to flexion, there was no significant difference found in four of five studies when examining flexion at end range. In some cases, previous research studies have noted inconsistent findings in the assessment of relative lumbar vs hip contribution to forward flexion. For example, Porter

&Wilkinson, (1997) witnessed a reduction in contribution of the lumbar spine while McClure et al., (1997) saw greater contribution from the lumbar spine through the mid range flexion in patients with LBP relative to healthy control participants (McClure, 1997). In addition to these relative displacement-based assessments, movement velocity and acceleration were also identified as a significant factor associated with LBP across seven studies (Esola et al., 1996; Hidalgo et al., 2012; Marras et al., 1995; McGregor & Hughes, 2000; Paquet et al., 1994; Wong & Lee, 2004; McGregor et al., 1997). These studies generally showed a significantly slower flexion speed and acceleration in subjects with LBP.

Finally, in the assessment of spine proprioception, a measure of postural awareness, many different approaches were taken throughout the scientific literature. These approaches include measures of position reposition accuracy, absolute error in repositioning, motion detection and motion precision. Across all categories, there was a significant decrease in the ability to find a specified pre-set angle in subjects with LBP, indicating a lowered proprioception in this group.

In some cases, researchers have also assessed the relative sequencing of spine movement within the spinal column during coordinated flexion-based movements. For example, a study by Gatton & Pearcy (1999) three unconstrained flexion tasks were analyzed and revealed four distinct lumbar movement patterns in healthy male and female participants with an approximate age of 30 years old. These movement patterns included "top down" (superior vertebral joints flex first), "bottom up" (inferior vertebral joints flex first), "all together" (vertebral flex in unison) and "middle last" (superior and inferior joints flex before the middle vertebral joints) (Gatton & Pearcy 1999). Similar findings have recently been reported in the assessment of multi-segment movement across the entire thoraco-lumbar spine (Beaudette et al., 2019). These studies suggest that the IVJs along the entire spinal column do not always flex concurrently during tasks flexion-oriented for all individuals, suggesting a wide range of potential motor control strategies.

Most of the research summarized above have assessed 3D relative spine kinematics. These measurements of 3D joint kinematics are typically described by Cardan/Euler angles. In addition, to flexion/extension-based movement assessments, axial rotation kinematics have been previously explored. Specifically, axial rotational measurements have been shown to vary based on position of the body as well as the anthropometrics of the participant (Fujii et al., 2007). Axial rotation of the lumbar spine has been demonstrated to be greater in the inferior lumbar IVJs than the superior IVJs when subjects' lower bodies were rotated up to 45 degrees as determined using magnetic resonance imaging (Fujii et al., 2007).

2.2 Conventional Laboratory Motion Capture Approaches

The study of *kinematics* is concerned with the quantification of movement, without consideration of the forces involved in the generation of such a movement. The goal of all motion capture technology is to evaluate *kinematics* of the body. Common parameters involved in the assessment of body kinematics include the acquisition of displacement, velocity, and acceleration data. In clinical and laboratory settings many non-invasive methods have been proven to be accurate in many contexts (Duc et al., 2014; Ferrario et al., 2002). These tools all have factors that affect their practicality in and out of lab settings. These factors can include physical size of the system, weight, cost, the requirement for specified training/knowledge, and sensitivity to environmental factors (Duc et al., 2014). For a system to be accepted as a laboratory standard they must be highly reliable and repeatable (Bolink, 2016; do Carmo Vilas Boas, 2019). When evaluating spine kinematics within a laboratory setting optoelectronic, electromagnetic, and inertial systems are the most typical methods to collect spine movement in healthy and LBP populations (Ferrario et al., 2002; Bolink, 2016, do Carmo Vilas Boas, 2019 & Ceseracciu, 2014).

2.2.1 Mechanical Motion Capture

Mechanical motion capture refers to motion capture techniques facilitated by an electrical transducer which is sensitive to changes in body positions and orientations. These large mechanical motion capture systems are typically less expensive than optoelectronic systems. A potentiometer functions through the use of a slider being moved along different locations of a resistive material, also known as a rotary resistor. The change in resistance is used to determine the location of the slider and therefore the angle of the system (Robertson et al., 2013). Another example of a mechanical system are strain gauges. These systems can also be used to measure joint rotation, such as lumbar spine flexion. This was shown in a study by Van Hoof et al. (2012) where lumbo-pelvic flexion was measured with a strain gauge based on individual total flexion in a group of cyclists. Strain gauges can measure joint rotation (e.g., percent flexion) through augmented resistance through the deformation of a sensor (Robertson et al. 2013). These systems typically have the disadvantage of needing to be connected to a collection system or computer with cables. They can also be bulky when worn by a participant and require precise application relative to an approximated joint center. This causes them to restrict and alter movement of the participant (Robertson et al. 2013). Most electrogoniometers and strain gauges are limited to the evaluation of 1D or 2D relative angles. Electrogoniometers have been used previously to measure spinal position and movement (e.g., Perriman, Scarvell & Smith, 2010; Dolan & Green, 2006; Robertson et al., 2013). Mechanical motion capture systems are not influenced by external interference due to light and other radiation like other optoelectronic systems.

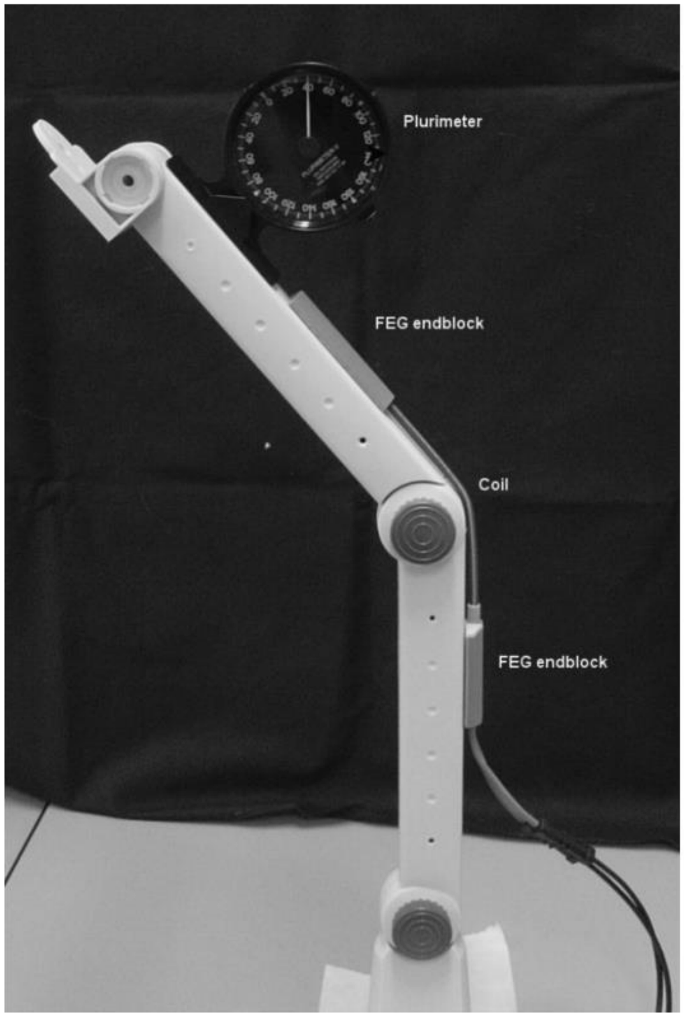

Figure 2: Pictorial depiction of an electrogoniometer validation setup against a plurimeter positioned to record the relative orientation of a moving segment. Two endblocks of the electrogionometer are rigidly attached to either segment about a simple 1D rotating hinge joint. Extracted from: Perriman, D. M., Scarvell, J. M., Hughes, A. R., Ashman, B., Lueck, C. J., & Smith, P. N. (2010). Validation of the flexible electrogoniometer for measuring thoracic kyphosis. *Spine*, 35(14), E633-E640.

2.2.2 Optoelectronic Systems

Optical motion capture refers to motion capture techniques that involve the use of multiple input sensors (i.e., cameras) in order to estimate 3D data (Hamill, Selbie & Kepple, 2013). Specifically, to resolve 3D coordinates, multiple cameras must be utilized to collect 2D data from markers (typically affixed to a participant's body segments) located within the capture volume. From these multiple 2D perspectives, 3D coordinates can be reconstructed in a common global coordinate system reference frame, meaning the global coordinate system remains static (Hamill, Selbie & Kepple, 2013). It is important to assume the body segments are rigid, to disregard the complex changes in viscoelastic soft-tissue deformation. This allows most optoelectronic systems to track the orientation of a segment using a representative local coordinate system throughout a dynamic movement. Some of these rigid segments can be denoted with clusters of markers which represent a gross average of multisegmented movement. This is especially true for segments such as the foot, pelvis, or ribcage, which are not rigid single anatomical segments. (Hamill, Selbie & Kepple, 2013). Some examples of optical motion capture manufacturers are Vicon, Qualisys, OptiTrack, and NDI (Optotrack), each of which can be used to track the spatiotemporal 3D locations of optical markers (NDI Optical Tracking Education Guide 2016). Optical tracking systems can be considered passive (retroreflective) or active (optoelectronic). Passive motion capture refers to a system that emits infrared (IR) light into a tracking area from the camera system. This area will allow for the IR light to be reflected back to the camera sensors off of specialized reflective markers within the tracking area (NDI Optical Tracking Education Guide 2016). Active optical tracking refers to a system that emits light from the markers to be detected by the camera. In each case, active and passive optical tracking technology utilizes emitted and reflected light from markers to triangulate a position of a marker within the tracking area using its X, Y and Z coordinates (NDI Optical Tracking Education Guide 2016). Typically, optoelectronic systems are limited to a specified tracking volume. Further, these systems can also be interfered with by other light sources and reflective surfaces, thereby generally limiting the use of these systems to indoor laboratory environments.

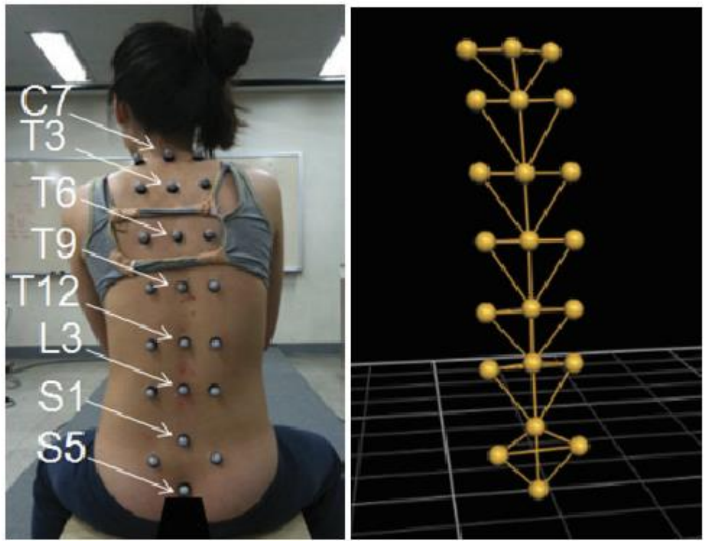

Figure 3: Pictorial depiction of a passive optoelectronic system used to assess the multisegmented movement of the spinal column. Extracted from: Noh, D. K., Lee, N. G., & You, J. H. (2014). A novel spinal kinematic analysis using X-ray imaging and vicon motion analysis: A case study. *Biomedical materials and engineering*, 24(1), 593-598.

2.2.3 *Electromagnetic Systems*

Electromagnetic motion capture refers to a motion capture system that utilizes the signals from a transmitter to create an electromagnetic dipole field. This range can vary based on the source and size of transmitter (Polhemus). These systems detect position of sensors within an electromagnetic field. These systems do not require markers to be exposed to a camera (Polhemus). This means the system can be placed under clothing and other wearable equipment and still detect the location of the sensors (Polhemus; Van der Kruk & Reijine, 2018). An example of the use of this technique is in the measurement of vertebrae movement in spinal restraints (Bell et al., 2009; Horodyski, 2011; Del Rossi, 2004). In a study by Bell et al. (2009), the electromagnetic sensors were used to evaluate C5-C6 flexion/extension restriction within ill fitting cervical orthoses (Bell et al., 2009). Unlike optoelectronic motion capture, these systems are not compromised by light sources, and do not require a direct line of sight. Despite this, environmental limitations can occur due to metal, and other ferromagnetic materials being within range of the transponders. Further, another limitation of electromagnetic systems is added signal distortion, which is typically associated with larger distances of a given sensor relative to the source of the electromagnetic field.

Figure 4: Pictorial depiction of an electromagnetic system to infer the 3D kinematics of C5-C6 intervertebral joint. Within this image, electromagnetic sensors (grey) are rigidly affixed to bone pins which have been implanted into the C5 and C6 vertebrae. Extracted from: Del Rossi, G., Horodyski, M., Heffernan, T. P., Powers, M. E., Siders, R., Brunt, D., & Rechtine, G. R. (2004). Spine-board transfer techniques and the unstable cervical spine. *Spine*, 29(7), E134-E138.

2.3 Alternative Portable Motion Capture Approaches

Beyond the use of the traditional motion capture systems, there are alternatives that may make the process of motion capture more affordable, cost effective, portable and may require less domain-specific technical knowledge regarding human anatomy and kinematic systems. These alternatives can be used to track segments of interest without all the components of traditional laboratory motion capture systems. The lack of cameras and markers can mean that there are no equipment restrictions due to lighting and other environmental factors. Further, many alternative systems do not have errors due to marker occlusion (Roetenberg, Luinge, Slycke, 2013). In general, the validation of these approaches in the assessment of spine kinematics is ongoing.

2.3.1 Inertial Systems

Inertial motion capture systems use small body sensors, sensor fusion algorithms, and biomechanical models to determine the position and orientation of body segments. Sensors such as accelerometers, gyroscopes, and magnetometers referred to as inertial measurement units (IMU) or more generally as microelectromechanical systems (MEMS) can process raw data streams directly on the sensor, or send data to be processed by computers, tablets, or smartphones. Measurements are made relative to a scaled and calibrated standard position (i.e., "I" or "T" pose or force of gravity) of a scaled kinematic model (www.metriainnovation.com). Inertial sensors are frequently used to measure ambulation (e.g., over-ground walking) and other types of movement. They utilize a combination of sensors to accurately determine segment position and orientation. Accelerometers are used to detect the linear acceleration of a sensor, including the approximate orientation of any gravitational acceleration. Gyroscopes are typically used to measure roll, pitch, and yaw rotational velocities (Brigante et al., 2011). Magnetometers act as compasses to provide information about the sensor's orientation relative to the Earth's natural magnetic field. These complimentary sensors can provide data to eliminate sensor drift; however, can be sensitive to ferromagnetic interference (Roetenberg, Luinge, Slycke, 2013). This type of motion capture is versatile because it can accurately track movement for entire bodies as well as single segments. The advantages of inertial motion capture include the multiple streams of information that come from its variety of MEMS sensors. However, there are also disadvantages to using inertial movement sensors. These can include restricted movement, predefined sensor positions and algorithms may not fit all participants the same, and potential drift issues associated with the integration and fusion of accelerometer data (Rebula et al., 2015). Further, IMU systems also may be sensitive to metal, which can potentially skew output data and typically capture data at a lower sampling rate relative to optical systems. Currently, one of the largest issues with both wearable and optical motion capture is that equipment is affixed to the skin. This means that skeletal movement must be inferred through the placement of the sensors on the skin surface. Due to this, soft tissue artifacts caused by tissue movement above the skeletal level can influence accuracy of signals derived from the skeleton (Mundermann et al., 2006). In human research, systems that require markers or sensors to be affixed to the skin can lead to augmented or unnatural human movement patterns. This could be avoided without the use of markers or other equipment placed on the body. This unnatural movement is referred to as artificial stimulus (Mundermann et al., 2006). Examples of these systems are the *MetaMotion Gypsy* (metamotion.com) and the XSENS MVN (Roetenberget al., 2013). These systems use and full body sensor networks to detect movement of the joints (Roetenberg, Luinge & Slycke, 2013). In a study by Beange et al. *Metamotion's* IMUs were used to measure local dynamic stability and continuous relative phase in the lumbar spine. This technology was concurrently compared to a Vicon optoelectronic system and validated its ability movement that effectively represents the lumbar spine (Beange et al., 2019). Another study utilized the XSENS bodysuit with 17 sensors. This experiment measured a wearable inertial motion capture system along with a spine motion composite index to evaluate fatigue on a visual scale. IMUs combined with the selected composite index scale determined that the system could effectively detect changes in spine motion caused by fatigue (Chan et al., 2020). Data can be collected outside of a lab/confined setting, so long as a receiver is in range. These wearable systems are typically accurate relative to their limbs in space, in a specific plane. This means the system cannot detect vertical or horizontal translation of the entire motion capture device relative to a global coordinate system not attached to the body. Therefore, these systems can only orient themselves against their own sensors, not in 3-dimensional space (Roetenberg, Luinge, Slycke 2013). This type of system is not disadvantaged by external interference due to light and other radiation occlusion like other optical based systems; however, as noted previously these systems can be affected by the presence of ferromagnetic interference when such materials are in close proximity to each IMU sensor. In general, inertial motion capture systems can be effectively used indoors and outdoors effectively (Roetenberg, Luinge, Slycke 2013).

Figure 5: Schematic depiction of an XSens MVN Link inertial system used to track the full 3D kinematics of various body segments. Inertial measurement units (IMUs – orange cubes) are affixed to specified anatomical segments which are calibrated to an anatomical model using measured scaling parameters and specified static poses (i.e. T-pose, depicted above). Sensor data are acquired by wearable data loggers and are wirelessly transmitted to a reciever. Extracted from: Roetenberg, D., Luinge, H., & Slycke, P. (2009). Xsens MVN: Full 6DOF human motion tracking using miniature inertial sensors. *Xsens Motion Technologies BV*, Tech. Rep, 1.

2.3.2 Computer Vision & Markerless Motion Capture

Markerless motion capture refers to a distinction of computer research utilizing computer vision, graphics, and other applications. This particular type of motion capture is useful in video games, medicine and sport sciences. The use of markerless motion capture has grown for clinical assessment. This includes clinically relevant differences in joint kinematics (Schmitz et al., 2014). Markerless motion capture removes the need for physical markers or sensors to be placed onto the body of the participant. This allows participants to act and move without equipment introducing potential artifacts and/or skewing movement patterns (i.e., artificial stimulus). A study by Schmitz et al. compared the accuracy between markerless and marker-based motion capture systems. It was found that there was an agreement between the markerless system against a marker-based system and a digital inclinometer, showing less than a 0.5 degree of difference during a controlled flexion, adduction and rotation task on a jig that simulated a ball and socket joint (Schmitz et al., 2014). Since markerless motion capture does not have the physical constraints of markers, there is a significant reduction in the time spent preparing the subject and placing markers on human models (Corazza et al., 2006). Any errors due to lack of visual information can also be combatted through the use of multiple cameras in the system to allow for redundancy, as cameras visualize the points of interest on a participant (Corazza et al., 2006). Previous work has used a single Microsoft Kinect camera with a depth sensor system and custom post processing software to determine the dimensional knee and hip angles in vivo, when a participant is performing a squat and measuring peak angles (Schmitz et al., 2015). This study showed agreement of less than five degrees difference between an optoelectronic motion capture system and the Kinect markerless system. The largest limit of agreement difference for the markerless system was 1.1˚ where the max acceptable value is 2˚. The single camera markerless motion capture system has the potential to provide data as a good proxy for significantly more complex and expensive marker-based systems in human subjects (Schmitz et al., 2014).

Many markerlerless motion capture systems are based on machine learning. Machine learning software allows a computer to learn and recognize characteristics of any input data. These characteristics are known as classifiers. A group of these classifiers together is known as an ensemble (Dietterich, 1997). Ensembles used for image recognition are more accurate than individual classifiers (Dietterich, 1997). In the case of markerless motion capture, pre training from an image network/or database should apply to the contents of the video being analyzed. This means pretrained data must be from a relevant ensemble to achieve a desired outcome. This includes studies on animal, human, and machine models. Using machine learning algorithms, the computer can learn constraints to implement, and features (i.e., anatomical landmarks) to identify when visualizing a model. In a study by Liu, Reibman and Boerman (2020), machine learning and motion capture was used on cattle to analyze behaviour through their movement. In this case, pre-trained data of the animal's body, leg and hoof regions was collected from video of the cattle to detect lameness. The data was analyzed by experienced farmhands for validation. Similar use cases exist for the tracking of human body segments. In many cases, an input image is screened by a convolutional neural network (CNN) which segments a time-varying input image to discern a region of interest to the image, the algorithm then identifies features within each region of interest based on what it has been taught and outputs anatomical locations with a confidence map. features (i.e., anatomical locations) identified with high confidence will be used to generate a skeleton to overlay on the output image (Liu, Reibman and Boerman, 2020). This technique utilizes the pre trained network which involves manually labelling relevant points of interest in order to develop network that can identify the same points on a time-varying set of images. In general, the more frames that are labelled, the greater the confidence of the algorithm and resulting anatomical accuracy of the labelled points. This approach to automatically identifying anatomical landmarks can be used with input data with varied pixel densities (i.e., resolutions) and colour concentrations (Xie et al., 2004). By varying parameters such as these most machine learning models are able to track points with greater accuracy. Computer vision programs such as DLC only require approximately ~200 labeled frames to achieve excellent tracking performance (Mathis et al. 2018). The combination of system accuracy and efficiency makes markerless motion capture an attractive alternative for general biomechanical purposes.

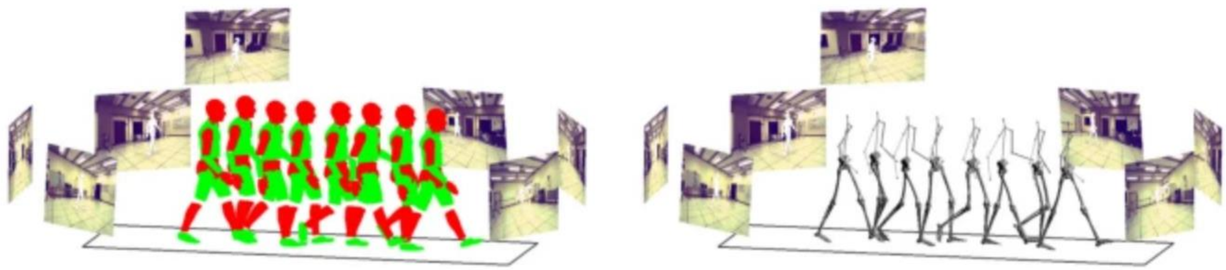

Figure 6: Left: Schematic depiction of markerless motion capture hulls being overlayed on top of a subject's body using an iterative closest point algorithm. Right: Schematic depiction of the assumed skeletal body segments creating a kinematic chain. Extracted from: Corazza, S., Muendermann, L., Chaudhari, A. M., Demattio, T., Cobelli, C., & Andriacchi, T. P. (2006). A markerless motion capture system to study musculoskeletal biomechanics: visual hull and simulated annealing approach. *Annals of biomedical engineering*, 34(6), 1019-1029.

2.3.3 Potential Benefits of Alternative Approaches

2.3.3.1 Cost

The cost of a motion capture system greatly varies by type and brand. In terms of wearable motion capture systems, Xsens motion capture suits can range from $12,500-$30,000 USD. This type of suit provides good versatility at a cost that is significantly less than the typical price of an optical motion capture setup (Xsens body suits are getting even better at motion capture engadget.com 2017). In terms of gold standard optical motion capture systems, full laboratory systems typically fall within the range of $30,000 - $100,000+ USD. Markerless motion capture stands to be the cheapest alternative motion capture system. A camera such as a Microsoft Azure DK is priced at $399 USD (microsoft.com). Software to interpret movement must be added to the price of the camera. Cost can be saved even further if selected open-source software can accept video from any camera.

2.3.3.2 Domain Knowledge

Domain knowledge refers to the knowledge required to operate the system. A Vicon optoelectronic system has components that are physical and virtual. These different components and their factors may have an influence on the accuracy and performance of the system (Windolf et al., 2008). These factors could include; marker material properties, optical projections, video conversion, camera configuration/orientation, lens distortion and calibration procedures. As compromises are made under many lab conditions, researchers may not be applying the most optimal parameters. They also may make small errors which may not optimize the systems ability to obtain the truest values when tracking points of interest (Windolf et al., 2008). Knowledge of anatomy is also highly important when considering the placement of markers or sensors on the body. In the case of traditional motion capture systems (where sensors and markers must be worn or affixed to the skin), artifacts of the skin must be considered and accounted for when placing markers. This means the location a marker is placed on the skin may not accurately represent a muscle or bony landmark when tracking (Lucchetti et al., 1998). Landmarking is a highly time-consuming task and requires a significant amount of anatomical knowledge in order to apply the markers in the correct locations. Therefore, when systems require both technical and anatomical knowledge, it can be challenging for researchers to account for all variables when trying to set up a complicated motion capture system. In general, markerless motion capture systems greatly simplify the amount of technical and anatomical knowledge needed to gather kinematic data.

2.3.3.3 Portability

Portability of motion capture equipment is a significant factor in the versatility of a system. The traditional optical motion capture systems tend to lack versatility as they require specialized locations and clothing to be functional when recording data. These requirements include a dedicated studio, non reflective clothing, and specialized markers to work properly (Kaimakis and Lasenby, 2004). Inertial and wearable systems are more portable than traditional optical systems, but they require wearable equipment to be transported. The sensors in wearable equipment may also be influenced by environmental factors such as temperature or the presence of ferromagnetic material. The presence of magnetic material may cause skewing of magnetometers (Roetenberg et al., 2013). Portability is a significant benefit of markerless motion capture systems. In the cases of both single camera and multiple camera systems, they provide additional portability and transparency that optical and wearable systems cannot offer (Kaimakis and Lasenby, 2004).

2.4 DeepLabCut (DLC)

DLC is a non-invasive motion and behavioural tracking tool, designed for human and animal pose estimation (Nath et al., 2018; Mathis et al., 2019). DLC utilizes computer vision algorithms to estimate movement. This is similar to the algorithms designed for other industries. Unfortunately, these other algorithms require thousands of labelled frames to be effective. In small experimental settings, this is less useful and inefficient (Mathis et al., 2018; Nath et al., 2018). DLC is designed to work from pretrained networks (designed to track specific anatomical landmarks on a human participant) to achieve its performance with one or more cameras, while also facilitating the use of custom marker sets which may vary depending on different experimental interests and or constraints (Nath et al., 2018; Mathis et al., 2018). This markerless pose estimation system facilitates analysis in fields of neuroscience, biomechanics, genetics, and more (Mathis & Warren, 2018), across a wide range of potential user-defined tracking landmarks.

2.4.1 Background & Pre-Trained Models

DLC was originally designed with the purpose of being used as a non-invasive motion capture system for animal behaviour research. The creators wanted to avoid other expensive marker-based systems that may be distracting to animals (Mathis et al., 2018). DLC has been historically used to extract key points on the anatomy of animals and humans. Specifically, relating to human subjects DLC is built around another algorithm called DeeperCut which is an adapted Deep Residual Network (ResNet) initially trained to identify human body segments using the publicly available ImageNet database. This particular technology is a state-of-the-art articulated multi character pose estimation software for human movement (Insafutdinov et al., 2016; Nath et al., 2018). Specifically, DeeperCut was designed to track human movement with a limited number of frames labelled by the user with great accuracy. This algorithm is well equipped to evaluate many human pose configurations (Insafutdinov et al., 2016); however, is limited to a set of *pre-defined landmarks* with notable exclusion of anatomical landmarks in the abdominal and chest region, required to analyze the motion of the spine.

Figure 7: Schematic depiction of DeeperCut's markerless motion capture algorithm identifying joint centers and limbs. The software visually overlays the images with coloured lines and dots (i.e., skeleton). This system is used to predict and track human movement. The absence of the spine in the body recognition should be noted in this image as the base of the neck splits down to the joint centers of the knees. Extracted from: Insafutdinov, E., Pishchulin, L., Andres, B., Andriluka, M., & Schiele, B. (2016, October). Deepercut: A deeper, stronger, and faster multi-person pose estimation model. In: *European Conference on Computer Vision* (pp. 34-50).

Pre-trained models are used to improve and achieve robustness in the system (Mathis et al., 2018). This means the points of interest on the model are picked manually on multiple frames by the user, these models are then referenced against a database for increased tracking performance. In previous research, it has been shown that pretrained features have improved performance in some human implications as well as in other species. This has typically been shown in human limb and facial tracking (Insafutdinov et al., 2017; Xiao et al., 2018). DLC can use one of two different architectures. These architectures are ResNet and MobileNet V2. They make up the autonomous potion of DLC that predicts the location of anatomical regions and fills the gaps between manually assigned frames (Mathis et al., 2019). Both of the architectures are pretrained on ImageNet (Mathis et al., 2019). ImageNet acts as an archive, or a massive object recognition benchmark. This database allows the software to make better inferences on a model when comparisons can be made to a large publicly available database (Mathis et al., 2018). ImageNet has been proven to increase within domain and out of domain performance, with a greater effect on out of domain applications (Mathis et al., 2019). These pretrained networks work alongside deconvolutional layers. This layering system is used to up-sample the provided video data and use it to derive probability densities. This allows the system to determine how confident it is in a body part being in a particular location. The systems probability density or confidence can be further increased by providing the system with more labelled frames (Mathis et al., 2018).

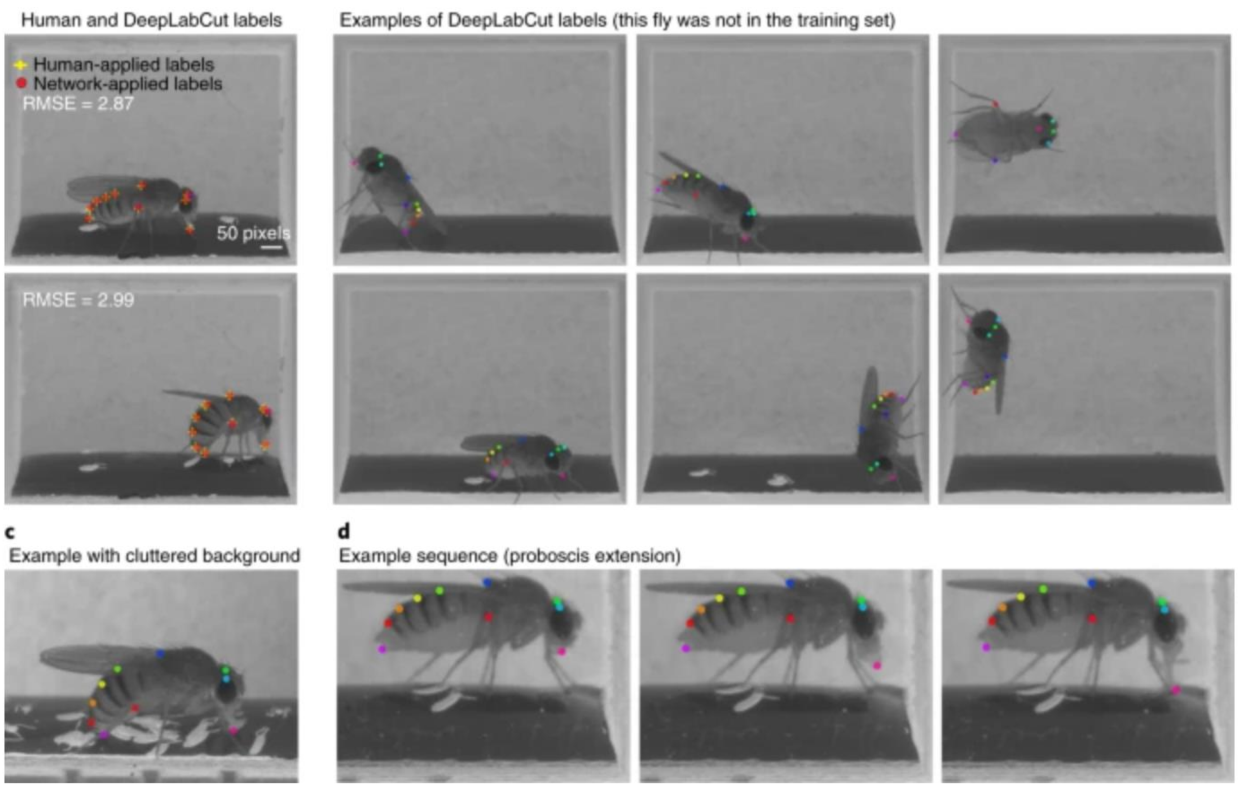

Figure 8: Schematic depiction of DLC overlaying its points of interest on images of a fly. This image depicts the robustness of DLC as the picture shows effective tracking of a fly not part of the training set, as well as a fly in a cluttered background that does not influence the marker placement. Extracted from: Mathis, A., Yüksekgönül, M., Rogers, B., Bethge, M., & Mathis, M. W. (2019). Pretraining boosts out-of-domain robustness for pose estimation. *arXiv preprint*, arXiv:1909.11229.

2.4.2 Validation & Typical Use Cases

In many cases, DLC is used for animal research and for collecting values relevant in animal neuroscience and behaviour (Mathis et al., 2018). Direct comparisons between DLC and other capture systems have not been tested. Instead, DLC has been validated by using its data to calculate normative values or clinical ratings (Williams et al., 2020; Fiker et al., 2020). Typical use cases for this software occur in mostly animal models (Labuguen et al., 2019; Fiker et al., 2020; Mundorf et al., 2020; Mathis et al., 2019). With DLC's flexibility to track a variety of user-defined landmarks across a wide range of applications and situations, very specific human movement can be measured. In a study by Williams et al. DLC data was compared to clinical parameters of individuals with Parkinson's disease, when measuring finger tap bradykinesia (Williams et al., 2020). Since DLC is also open-source software, it can be altered to more effectively be used in specific applications. In a study by Fiker et al. Visual Gait Lab was utilized, which is a variant built on the framework of DLC (Fiker et al., 2020). This version of DLC is streamlined for easy setup, use and download. This software is designed to generate gait measures on a mouse model. This demonstrates DLCs versatility as open-source code.

2.4.3 Considerations for Accuracy and Precision

When validating a novel computer vision model such as DLC, two parameters which need to be considered are both accuracy and precision, with respect to some accepted gold standard. In a set of measurements *accuracy* is the closeness of a measurement to a specific gold standard value, whereas *precision* is the closeness of repeated measurements to each other. Given this, *accuracy* can be described by "trueness", whereas precision can be considered the range of "uncertainty" (Eichelberger et al., 2016). Generally, measures of accuracy are depicted as mean differences between a novel approach with respect to a gold standard. Measures of precision are related to variability (e.g., standard deviation). As described by Harsted et al. (2019) the precision in their study was defined by the differences between the upper and lower levels of agreement (upper limit – lower limit).

Both accuracy and precision can be impacted by a variety of factors including, but not limited to, the size of the motion capture volume, the velocity of the movement, and any potential soft-tissue artefacts generated during a dynamic movement (Bolink et al., 2016). For example, in a study by Xu et al. (2015), it was demonstrated that different levels of walking parameters have showed different levels of agreement between markerless systems and an optoelectronic system (Optotrak Certus System, Northern Digital, Canada). There were different body segments that would fall into the acceptable range of five degrees while some parameters varied outside of the clinically acceptable levels of agreement (Xu et al., 2015). This demonstrates that the accuracy of the system can vary based on the segment in question. For the purposes of this research, accuracy is based solely on the agreement between the motion capture algorithm (e.g., DLC) and the gold standard motion capture system (e.g., Vicon) for the segments and movements being analyzed. In general, this method of validation, against a gold standard, can occur in two different ways. One of the ways includes assessing a system in a controlled environment. The second is performing the assessment in an uncontrolled environment (Beange et al., 2019). The first approach allows researchers to remove potential sources of errors, the second approach allows for validation of the motion capture method in more ecologically relevant scenarios.

2.4.4 Benefits of DLC

There are many advantages of DLC over other markerless systems. These include; advantages in flexibility, functionality, efficiency and knowledge required to use the system. Some of the main benefits of using DLC is how the code is designed to streamline work for the researcher. The labeling procedure is made easy with step-by-step instructions. This labeling can then immediately be used for automated pose extraction (Nath et al., 2018). There are only a small number of training images required to achieve human level accuracy, mitigating the cost of manual behavioural analysis. An obvious physical benefit of DLC is, it does not require physical markers to track specific points of interest (Nath et al., 2018). DLC can effectively analyze movement across different species. Meaning, it gains more utility as it works on humans as well as many novel animal models. This also means arbitrary and flexible marker models can be achieved. DLC is robust and can learn to detect points of interest in conditions that are not ideal. This includes poor lighting or lens distortions. This also applies in terms of colour contrasts and environment. A plain lab setting is not required to track points of interest (Nath et al., 2018). DLC can also be used in more advanced applications than single camera setups. Multiple networks can be individually trained for different cameras simultaneously. This can allow for three dimensional coordinates to be calculated and resolved. The cameras used to capture data for DLC do not need to be specialized. Most consumer grade cameras can effectively be used (Nath et al., 2018).

2.4.5 Gaps in the Literature and potential utility for DLC when Evaluating Spine Kinematics

To our knowledge, there remains to be a gap in the literature of where markerless motion capture systems are used to measure the human spine. The spine is not as visible and easily distinguishable as the extremities, as the software typically looks for edges in the model for information (Insafutdinov et al., 2017). This complexity when measuring the spine may come from its size, multiple segments, geometry, and the muscles it resides beneath (Robin et al., 1994; Gregory, Cramer and Darby, 2017). This gap in the literature neglects computer vision as a way to specifically measure spine kinematics. Due to DLC's ability to track within domain and out of domain data (Mathis et al., 2019), the algorithm is well equipped to measure arbitrary novel data and marker sets. This means the software is capable of measuring and interpreting data that DLC has been trained with (within domain) as well as applying training to different sets of data (out-of-domain). The ability to train DLC on any movement may assist in detecting movement in the lumbar spine.

Another gap in the data stems from validation. At this time, to our knowledge there are no studies that have concurrently validated the markerless motion capture system DLC vs gold standard motion capture systems when tracking any movements of the body. Conducting research on this topic may facilitate future studies to be potentially more confident in DLC's capabilities when measuring spinal movement.

Table 1:Advantages and Disadvantages of Common Kinematic Systems

	Mechanical Motion Capture	**Optoelectronic Systems**	**Electromagnetic Systems**	**Inertial Systems**	**Computer Vision & Markerless Motion Capture**
Advantages	Accurate for Lumbar/Thoracic spine Relatively inexpensive Real time data output No occlusion	Gold standard in lab settings Can track translation within the capture volume High capture frequency	Accuracy not influenced by infrared light Real time data output No occlusion	Various sensor systems collect an abundance of data Some systems are wearable Large capture area compared to optical	Inexpensive Useful and effective tracking novel models Non invasive (No markers) Little to no anatomical knowledge required Streamlined user friendly interface
Disadvantages	Cumbersome Large some sensors can be influenced by ferromagnetic environment. Anatomical knowledge required for landmarking	Limited capture volume Expensive Accuracy affected by infrared lighting and reflective clothing Requires controlled environment Anatomical knowledge required for landmarking Rigid bodies assumed	Accuracy influenced by distance away from its base Anatomical knowledge required for landmarking Small capture volume	Restricted movement from sensor devices cannot track translation relative to coordinate system Predefined marker models Some sensors influenced by metal Positional/segment drift.	Powerful computer component required to train models can be expensive

Table 2: Sensors, Specifications, Placement and Outcome Measurements

Article	Unit(s)	Type of sensor	Sample Frequency (Hz)	Placement	Measurement outcomes
(Gatton & Pearcy, 1999)	5 Sensors	A Motion Star motion analysis system (mechanical)		$L_{3/4}$, $L_{4/5}$ and L_5/S_1	percentage of spinal flexion
(Duc et al., 2014)	2 Sensor 4 Markers	Physilog®, BioAGM, CH (Inertial) Vicon T40S (Optoelectronic)	200 200	Forehead, sternum four-marker cluster was attached to the head with a helmet, sternal manubrium, the xyphoid process and the spinous processes of the second and seventh thoracic vertebras	Flexion/Extension Axial Rotation Lateral Bending (C4–C5, C5–C6 or C6–C7)
(Bolink et al., 2016)	Sensors Markers	MicroStrain® Inertia-Link® tri-axial magnetometer, triaxial gyroscope and tri-axial accelerometer (inertial) Vicon	100 200		step frequency mean step time mean step length Sagittal Plane ROM RMSE (Cervical Spine)
(Ceseracciu et al., 2014)		An 8-camera SMART-D stereophotrogrammetric (optoelectronic system) Markerless motion capture	200 100	Proprietary gait model	Hip, knee and ankle joint angle RMSD
(Perriman et al., 2010)	2 Sensors	Biometrics flexible electrogoniometer (mechanical)	NA	T6-T7 and T12	FEG angle and plurimeter angles Cobb Angle

(Bell et al., 2009)	2 Sensors	One Nest of Birds (NOB) electromagnetic sensor (Ascension Technology) (electromagnetic)	NA	Head, upper back	CRoM (Cervial Range of Motion)
(Horoduski et al., 2011)	2 Sensors	Liberty motion analysis device (Polhemus)	240	C5, C6 vertebral bodies	Flexion, extension, right bend, left bend, right rotation, left rotation
(Beange et al., 2019)	2 Sensors	MetaMotionR IMU	100	T_{10}-T_{12} spinous processes, sacrum	Kinematic data Euler data relative motion estimates Local dynamic stability Thoracic and Sacral time Series
(Chan et al., 2020)	17 Sensors	Xsens MVN	240	Head T8 vertebrae Pelvis bilaterally on the shoulders upper arms forearms hands thighs shanks feet	Range Peak Orientation Angular Velocity Angular Acceleration
(Schmitz et al., 2014)	0 10 Markers	Microsoft Kinect (Markerless) Motion Analysis Corp (optoelectronic)	30 200	Simulated Ball and socket joint resembling a knee Markers on thigh and shank	Flexion–extension and ab–adduction angles in simulated ball and socket joint
(Liu et al., 2020)	0	Regular surveillance camera (Markerless)		Head, Nose, top of neck, spine Tailhead, mid thigh, bottom of shoulder plus 8 leg and hoof points	spatial location of the body region detailed positions of body parts
(Mathis et al., 2019)	0	Camera Type not listed (Markerless)	NA	22 labeled body parts	percent correct keypoints Transfer learning gain

(Fiker et al., 2020)	0	Camera type not listed (Markerless)	NA	Nose, FrontRight1 FrontRight2 FrontLeft1 FrontLeft2 MidPointRight MidPointLeft HindRight1 HindRight2 HindLeft1 HindLeft2 Rear	Number of strides Average stance duration Average swing duration Average stride duration Percentage stance Percentage swing Swing to stance Stride frequency Stride length variability Gait Symmetry Paw angle

*NA = information not listed in article

CHAPTER III: METHODOLOGY

3.1 Participants

A convenience sample of participants was recruited via poster or word of mouth at Brock University. To be eligible to partake in the research study, participants had to be between 18-30 years of age and free of any musculoskeletal or neuromuscular disorders affecting the control of their body movement. Specific exclusion criteria included: (1) the report of low back pain within the past three months, (2) the report of any neurological (e.g., concussion within the past six months, Parkinson's disease, Amyotrophic Lateral Sclerosis, Multiple Sclerosis, vertigo, etc.), orthopedic (e.g., recent fracture, osteoporosis, osteoarthritis, etc.), muscular (e.g., recent sprain, strain, or tendonitis, muscular dystrophy, etc.), or hearing disorders and (3) current upper respiratory infection that may interfere with their balance and mobility and participants. Furthermore, participants could not report any known allergies to rubbing alcohol or adhesives due to the need to affix experimental equipment to the skin surface. To screen for the inclusion and exclusion criteria, all participants completed a general heal screening questionnaire (Appendix A) and sign informed consent (Appendix B) prior to data acquisition. The proposed protocol was approved by the Brock University Health Sciences Research Ethics Board (HREB), in accordance with the Declaration of Helsinki. A copy of the approval certificate has been appended to this thesis (Appendix C).

3.2 Materials

To track spine and upper extremity kinematics a passive retroreflective motion capture system, with time-synced reference video was used (8 x Vicon Vero 2.2, 1 x Vicon Vue, Vicon Motion Systems Ltd.). Seven 1 cm diameter spherical, retroreflective markers were affixed to specific palpable bony anatomical landmarks (humeral head [HH], humeral lateral epicondyle [HLE], radial styloid process [RSP]) or rigid bodies (T12 and S1) (Figure 9). Prior to the arrival of a participant, all equipment was calibrated and aligned appropriately. All raw retroreflective kinematic data were sampled at 100 Hz, labelled and gap-filled in Vicon Nexus software. Concurrent video data were also acquired at 100 Hz. 3D optical kinematic data obtained from Vicon Nexus were exported in an ASCII (.csv) format. Time-synced 2D video data were compressed (Cinepak) and subsequently exported in a video (.avi) format.

Figure 9: A pictorial depiction of the harness straps used to secure the fins over the T12 and S1.

3.3 Experimental Protocol

Upon arrival to the research laboratory, participants were required to first sign informed consent (Appendix B) and complete a general health history survey (Appendix A), which included a self-report of the participant’s age, height, and mass. Upon completion, participants were instructed to change into athletic clothing to facilitate the placement of any experimental equipment. To track the flexion-extension rotational kinematics of the lumbar spine and elbow two approaches were taken. To track the upper-extremity single reflective markers were placed superficial to specific bony landmarks (HH, HLE, RSP). To track the lumbar spine rigid dorsal fins, consisting of two reflective markers, were used to approximate the local sagittal axis at specific spinal levels (T12, S1) (i.e., Beaudette et al., 2014). Each dorsal fin was affixed to the participant by using adjustable straps placed over the shoulders and around the waist/ribcage (Figure 9). Once all kinematic markers and rigid bodies were affixed to the participant, two calibration movements were acquired including (1) a static standing trial, and (2) a dynamic spine and elbow movement trial. During this process data quality will be assessed, and once data quality has been confirmed, the experimental protocol began. Both the static standing trial and dynamic movement trial were used to improve marker tracking in Vicon Nexus. Further, the dynamic movement trial, which consists of max-ROM flexion extension movements of the elbow and spine, was be used to train any subsequent DLC deep neural networks.

The experimental protocol consisted of two movement tasks (maximal and submaximal repeated flexion). Both tasks were completed at both the lumbar spine and elbow. First, each participant completed a maximum flexion range-of-motion (Max-fROM) task for both the lumbar spine and elbow. To accomplish this task participants were instructed to begin by standing in a neutral upright posture. For the elbow Max-fROM task, participants were instructed to flex their elbow in a slow and controlled fashion until a maximum perceived flexion magnitude was obtained. Once this maximum flexion was attained, participants were instructed to slowly extend their arm towards their original neutral posture and repeat this Max-fROM movement two more times consecutively. Similarly, for the spine Max-fROM movement participants were instructed to begin in a neutral standing posture while maintaining their arms crossed against their chest for the duration of the movement. From this neutral posture participants were instructed to slowly flex through their lumbar spine until maximum perceived flexion motion was achieved. Once this posture was attained, participants were instructed to slowly extend back to their neutral standing posture, before completing the Max-fROM movement two more times consecutively. Upon completion of the Max-fROM trials, repeated submaximal flexion trials (submax-fROM) were completed. For these trials participants were instructed to repeatedly flex their elbow and spine (30 times total). During these movements participants were provided with specific targets to contact (either with their hand or torso) and were instructed to move at a pace which was controlled using an auditory metronome (four seconds/movement – two seconds per flexion, two seconds per extension). Submax-fROM trials are being retained for future research related to elbow and lumbar spine motor control and coordination. For the purposes of the current work, only Max-fROM trials were analyzed.

3.4 Data Processing

3.4.1 DLC Coordinate Extraction

The following compressed videos were exported from Vicon Nexus for further analysis: (1) dynamic movement trial, (2) elbow Max-fROM, (3) elbow Submax-fROM, (4) lumbar spine Max-fROM, and (5) lumbar spine Submax-fROM. As noted previously, the dynamic movement trial was used to train any DLC model(s), with these models subsequently being used to evaluate the anatomical coordinates for each fROM trial.

At this stage of data processing the participants in the study were evenly partitioned into two groups. This was done to compute the relative accuracy and precision of DLC in evaluating participants which were used in the training of a DLC model, and for *new* participants, which were not used to train the model. These groups include a training and testing groups. Specifically, participants in the training group were used to develop a configuration file to be implemented into the DLC algorithm. Further, the dynamic movement videos from this training group of participants were manually labelled to derive a training dataset. No data from the testing group was used in the training of the DLC algorithm for the current study. By taking this approach, the researchers could quantify the accuracy of DLC in evaluating new data, and understand if such ‘new’ data can influence the performance (i.e., accuracy and precision) of the algorithm relative to a Vicon retroreflective gold standard.

To develop a DLC model from the training dataset, a configuration file was first automatically generated by the DLC graphical user interface (GUI) and subsequently edited to specify the parameters required to facilitate further analyses. The changes made to the configuration file include the specification of each “body part” required for the analysis and altering the number of training frames (n = 100 per participant in the training dataset) that DLC extracts from the video corresponding to each participant’s dynamic movement trial to be manually labelled. Next, DLC was used to extract frames from each dynamic movement trail in the training dataset using the k-means function based on the specifications (i.e., number of labelled frames) in the configuration file. Specifically, the k-means approach was used to optimize the separation between labelled frames to ensure the most diverse postures are used for labelling. In general, k-means algorithms are unsupervised machine learning techniques which cluster data to ensure that clusters of information are grouped properly. In this research DLC was relied on to automatically select images from the input videos (training group) that were significantly different from one another before labelling. This ensures that once all the selected frames were labelled manually, the configuration file does not have an excessive number of labelled frames from the same or similar images across the time series. Once the frames were extracted for each participant in the training group, frames were labelled manually for each "body part" specified within the configuration file. For the purposes of this research these body parts included the kinematic markers placed on each participant. To evaluate the accuracy and consistency of the manual labelling process of the specified body landmarks, the DLC graphical user interface applied virtual markers, graphically, to the labelled frames assessed from the dynamic calibration trial. Once frames were manually labelled, the researcher must select "check labelled frames". This ensured that DLC applied the virtual points to the selected frames. Manually labelled frames extracted from this dynamic calibration video were subsequently used in combination with an existing neural network architecture (i.e., ResNet, MobileNet) to facilitate the evaluation of new unlabelled trials (from either training or testing group), which have not been included in the model training process. The neural network architecture used in the current analysis was ResNet-50 architecture. This represents an existing convolutional neural network architecture that is 50 layers deep, which can be subsequently trained using the extracted labelled frames. When training this neural network, values applied to iteration preferences included display iterations are set to 100, save iterations are set to 500. This allowed the user to monitor the training progress, and for the algorithm to incrementally update throughout the training process. For the purposes of the current project, the number of iterations desired was set to a minimum of 500,000. Once the DLC model was trained it was subsequently used to evaluate unlabelled videos from the all Max and Submax-fROM experimental trials (in both the training and testing group of participants). In analyzing these videos, the DLC algorithm exports an ASCII (.csv) file with the tracked 2D coordinates (in pixels) of each body part (i.e., kinematic marker) and the associated likelihood of each marker being located at the specified location within each frame of the input video.

3.4.2 Post-Processing and Extraction of Planar Anatomical Angles

Post-Processing of all Max and SubMax fROM data from both DLC and Vicon was completed in MATLAB (2020b, The Mathworks Inc.). Given the assumption that the global frame of all 3D Vicon data is in alignment with the camera frame 3D Vicon data was reduced to 2D (representing the approximate sagittal plane of the participant) for further analysis (i.e., Howarth, 2014). First, all 2D DLC and Vicon coordinates were filtered with a 4th order, zero-lag Butterworth filter with an effective low-pass cut-off of 6 Hz. Next, the 2D coordinates were used to define the relative orientation of the humerus, forearm, T12 vertebra, and S1 vertebra within the sagittal plane. Once completed, these relative orientations were compared to evaluate the planar angle between the appropriate segments during each movement task (i.e., elbow or lumbar spine) using a 2D dot product (i.e., Figure 10). Repeated cycles of each Max-fROM trial (n = 3) were time-normalized from 0-100% of a cycle (101 frames), for the elbow and lumbar spine representative of the relative joint angles extracted from DLC and Vicon during each Max-fROM cycle. The ensemble waveforms derived from the elbow and lumbar spine were be used to quantify the accuracy and precision of data evaluated using DLC against those evaluated using Vicon. Specifically, accuracy was quantified by observing the relative difference between planar elbow and spine flexion-extension data evaluated using DLC and Vicon, respectively. In contrast, precision was quantified in two ways. First, the (n = 3) standard deviation was quantified for each participants Max-fROM trial to estimate cycle-to-cycle variability. This variability was compared between DLC and Vicon, and a larger variability was interpreted as a reduced cycle-to-cycle precision. Second, the variability in distribution of DLC-Vicon errors were inspected using Bland-Altman analysis, while accuracy was represented through any mean Bias, between-subject variability (i.e., precision) was inferred from the levels of agreement.

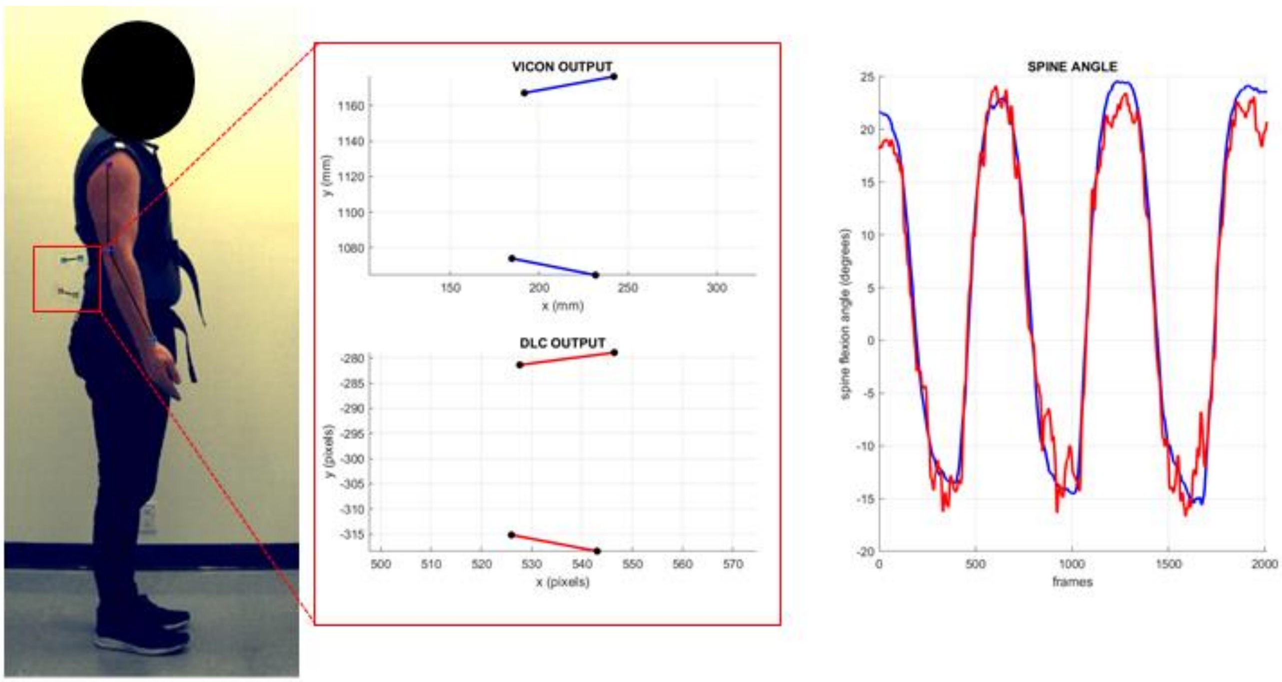

Figure 10: Depiction of the experimental setup showing a single frame from a dynamic movement trial, with each marker identified (left), the resulting sagittal orientation of the T12 and S1 vertebra (middle) and the computed angle (right) for the data derived from Vicon (blue) and DLC (red).

3.5 Statistical Analysis

All statistical analyses were completed in MATLAB (2020b, The MathWorks Inc.). Specifically, a statistical parametric mapping (SPM) approach was used to analyze computed ensemble mean and standard deviation time-varying data as a measure of DLC accuracy and precision relative to the Vicon gold standard data. Given this, the dependant variables for the SPM analyses included either the computed planar angles, or the cycle-to-cycle (i.e., standard deviation) variability waveforms. The independent variables for the current analysis included the group (i.e., training vs. testing) or motion capture modality (i.e., Vicon vs. DLC). Higher-order interaction effects were also analyzed. Prior to any parametric analyses, the normality of model residuals was assessed using a SPM X^2 test. For all SPM analyses, a scalar output statistic (i.e., SPM{F}) was computed for each time-point. The calculation of SPM{F} indicates the magnitude of difference between input waveforms (i.e., mean or SD), and the interpretation is comparable to a conventional F-statistic. To test the null hypothesis (i.e., that no significant difference exists between DLC and Vicon) the critical threshold (F^*) was calculated at which 0.5% of smooth random curves were be expected to traverse (i.e., α=0.005), which was used to designate supra-threshold clusters, or areas of the difference within the time-domain between independent variables. Conceptually an SPM ANOVA is like the calculation and interpretation of a scalar ANOVA. If the SPM{F} trajectory crosses the critical threshold (F*) at any time point the null hypothesis is rejected. All SPM analyses was implemented using the open source spm1d code (v.M.0.4.5, www.spm1d.org) in MATLAB.

To compliment the SPM analyses, linear regressions were also computed to infer the relative effects of sagittal plane misalignment (i.e., between DLC and Vicon) on the computed accuracy measures. Specifically, differences were computed between DLC and Vicon for each time-point of every flexion cycle across all participants. In addition to this, the relative rotation of each body segment was computed by evaluating the dot product of each segment with respect to the Vicon global anterior-posterior axis. This angle represents a transverse offset, or the relative angle between each participant’s body segment of interest (i.e., arm, lumbar spine) relative to the assumed Vicon sagittal plane. The transverse offset data were plotted against the computed differences between Vicon and DLC, and a linear regression was fit to understand if any systematic differences in error were present, potentially linked to the relative posture (i.e., alignment) of the participant within the 3D Vicon camera volume.

CHAPTER IV: RESULTS

Sixteen participants (seven males, nine females) volunteered to participate in the research study. All participants were free of any musculoskeletal or balance disorders at the time of testing. Due to issues in the tracking of optical kinematic data two participants were excluded from any further analyses resulting in a total sample size of 14 participants (Table 3). The remaining sections were structured to present data relating to DLC accuracy and cycle-cycle variability (i.e., precision), in the estimation of planar elbow and lumbar spine angles, relative to the retroreflective Vicon gold standard. Supplemental analyses have been included to assess common trends in the accuracy and precision of DLC over the course of spine and elbow flexion extension movements, in addition to the assessment of any systematic effects related to the misalignment of body segments relative to the idealized Vicon global sagittal plane. All data are presented as means ± standard deviations. For any graphical comparisons, data obtained from Vicon are presented in blue, and those from DLC are presented in red.

Table 3. Participant Demographic Information

Parameter	Training Group	Testing Group
Number (n)	7	7
Sex (m/f)	4/3	2/5
Age (years)	24.28	21.85
Height (cm)	174.28	167.36
Mass (kg)	71.8	71.9

4.1 DeepLabCut vs. Vicon Accuracy

A visual depiction of the time normalized ensemble flexion-extension waveforms for all participants and all Max-fROM cycles is depicted in Figure 11. As expected, the planar flexion-extension ROM is larger, and more consistent for the elbow joint relative to the lumbar spine. In the subjective appraisal of these data, it is clear that DLC (red) and Vicon (blue) show good agreement in the estimation of time-varying planar elbow (Figure 11A-B) and spine (Figure 11 C-D) angles. When assessing mean waveform data (bolded lines), an apparent systematic bias is introduced in the testing data (Figure 11 B,D) relative to the training data (Figure 11A,C). Specifically, within the testing group, it appears as if DLC results in a systematic 1-3^{o} under-estimation of the elbow flexion angle during the entirety of the flexion-extension movement. Further, for the estimation of spine flexion-extension within the testing group, there is an apparent 5-8^{o} over-estimation of the spine flexion angle during the entirety of the movement.

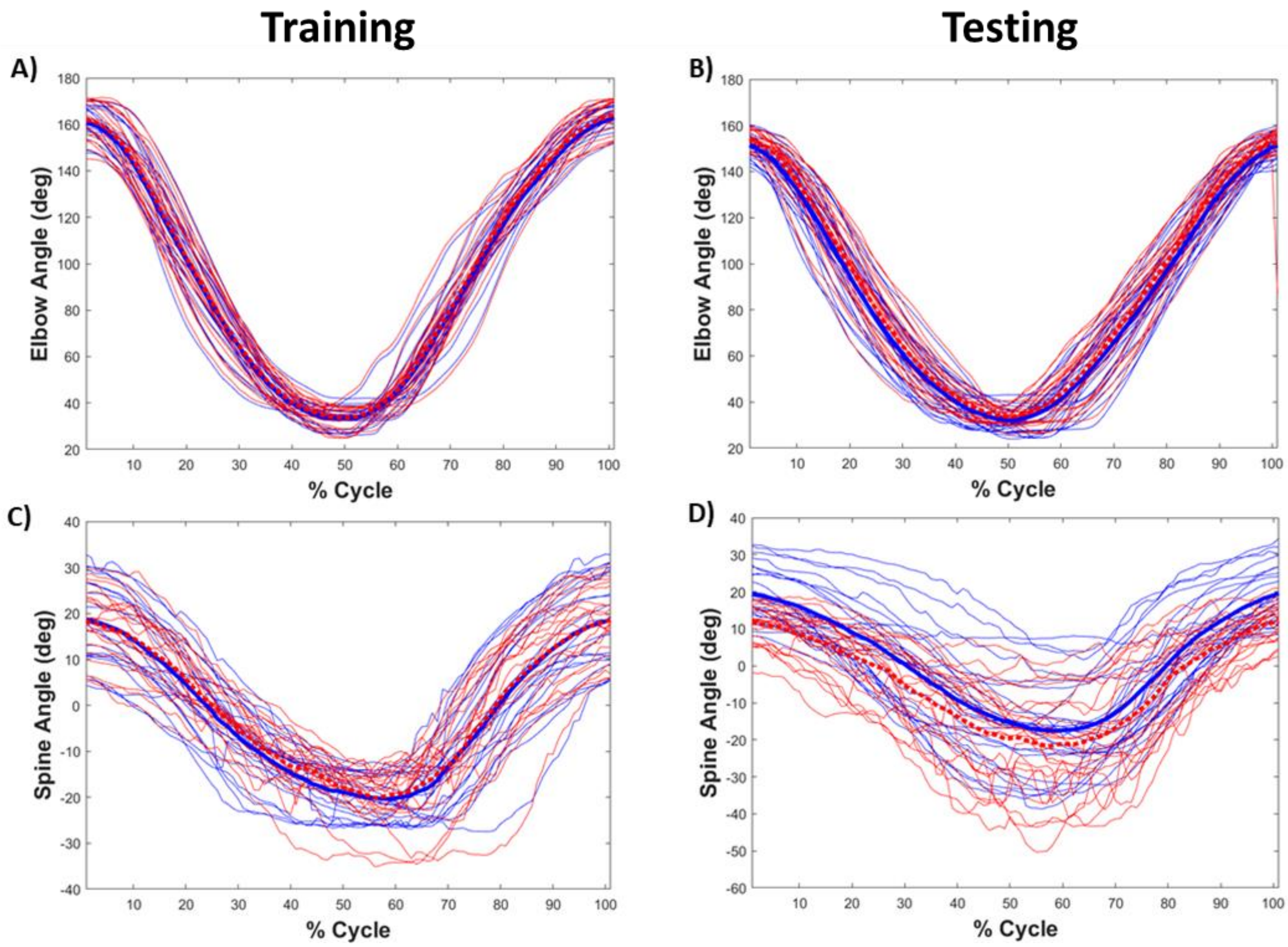

Figure 11. Planar angle time series data for each flexion-extension cycle from each participant for elbow (A,B) and spine (C, D) Max-fROM. Data are separated based on those allocated to the training group (A, C) or testing (B, D) groups for both DLC (red) and Vicon (blue). Averages for each motion capture modality are bolded.

Prior to statistical comparison of ensemble flexion-extension waveforms, the normality of residuals was assessed using a SPM X^2 test. The results from this test are depicted in Figure 12. With the exception of a small suprathreshold cluster, exceeding the critical SPM{X^2} between 45 – 50% for the time-varying elbow flexion data, all remaining elbow and spine flexion-extension waveform data residuals were normally distributed. As such, parametric assumptions were confirmed, and a two-way SPM ANOVA was subsequently implemented on the dataset.

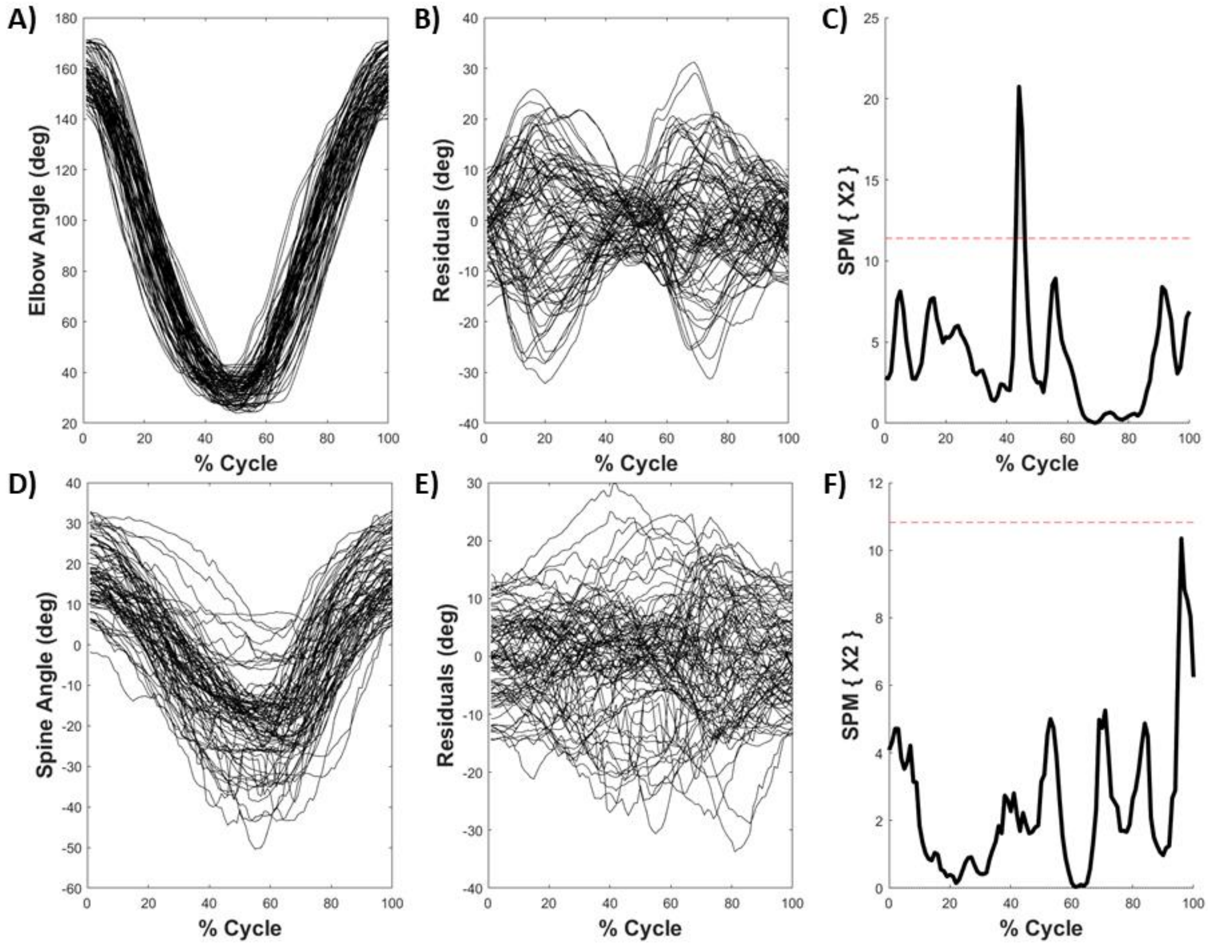

Figure 12. Visual representation of Elbow and Spine angle relative to % Cycle, Residual Values and SPM{X^2} Normality tests for the elbow (A-C) and spine (D-F).

The results of the two-way SPM ANOVA are depicted in Figure 13. Specifically, SPM{F} tests were completed to detect significant differences between the training vs. testing sets, capture methods (Vicon vs. DLC), as well as any potential higher order interaction effect between these independent variables. Significant differences were only found between the Testing Set vs. the Training Set when analyzing the elbow (critical F^* = 9.102). Specifically, a suprathreshold cluster was observed between 0% and 12% in the early phase of elbow extension ($p = 0.007$), and between 63% and 100% in the later phase of elbow flexion ($p < 0.001$). The spine data showed no significant results were found when comparing training to testing set or capture methods (critical F^* = 8.519). There were also no significant interaction effects between the training/testing dataset and motion capture modality (i.e., DLC vs. Vicon) detected for the planar angles computed for the elbow and lumbar spine (Figure 13).

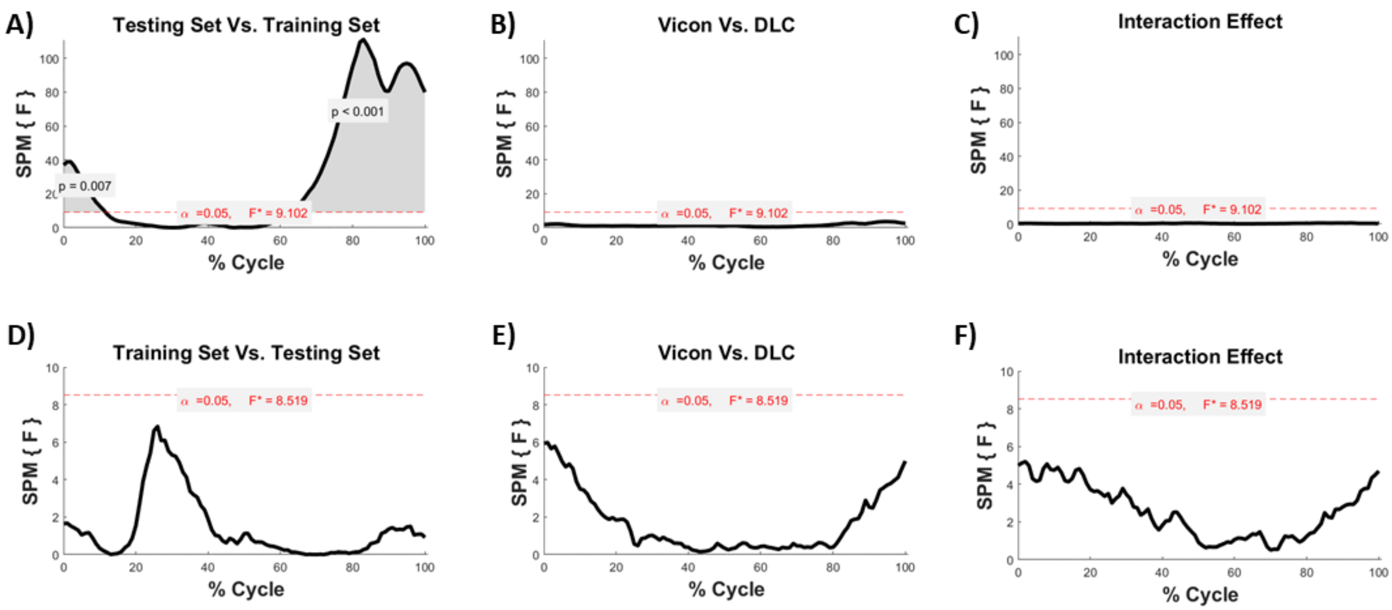

Figure 13. SPM two-way ANOVA main effects results including Training Vs. Testing datasets, capture methods (Vicon Vs. DLC) and the interaction effects for elbow (A, B, C) and spine (D, E, F).

4.2 DeepLabCut vs. Vicon Cycle-Cycle Variability

A visual depiction of the within participant, three-cycle standard deviations obtained during the Max-fROM trials are depicted in Figure 14. Specifically, cycle to cycle variability is depicted for each subject across the elbow (A, B) and spine (C, D) for the training (A, C) and testing (B, D) groups. Upon visual inspection, it is clear that a larger degree of cycle-cycle variation was observed during the flexion and extension phase of each elbow/spine movement, and that this variability was systematically reduced as each participant approach their neutral or flexion end-range posture. Notably, a larger magnitude of mean cycle-cycle variability was observed in the estimation of planar elbow angles, rather than in the estimation of planar lumbar spine angles. No apparent visual differences were observed in the comparison between the testing and training dataset, nor in the comparison between DLC and Vicon, for both the elbow and lumbar spine.

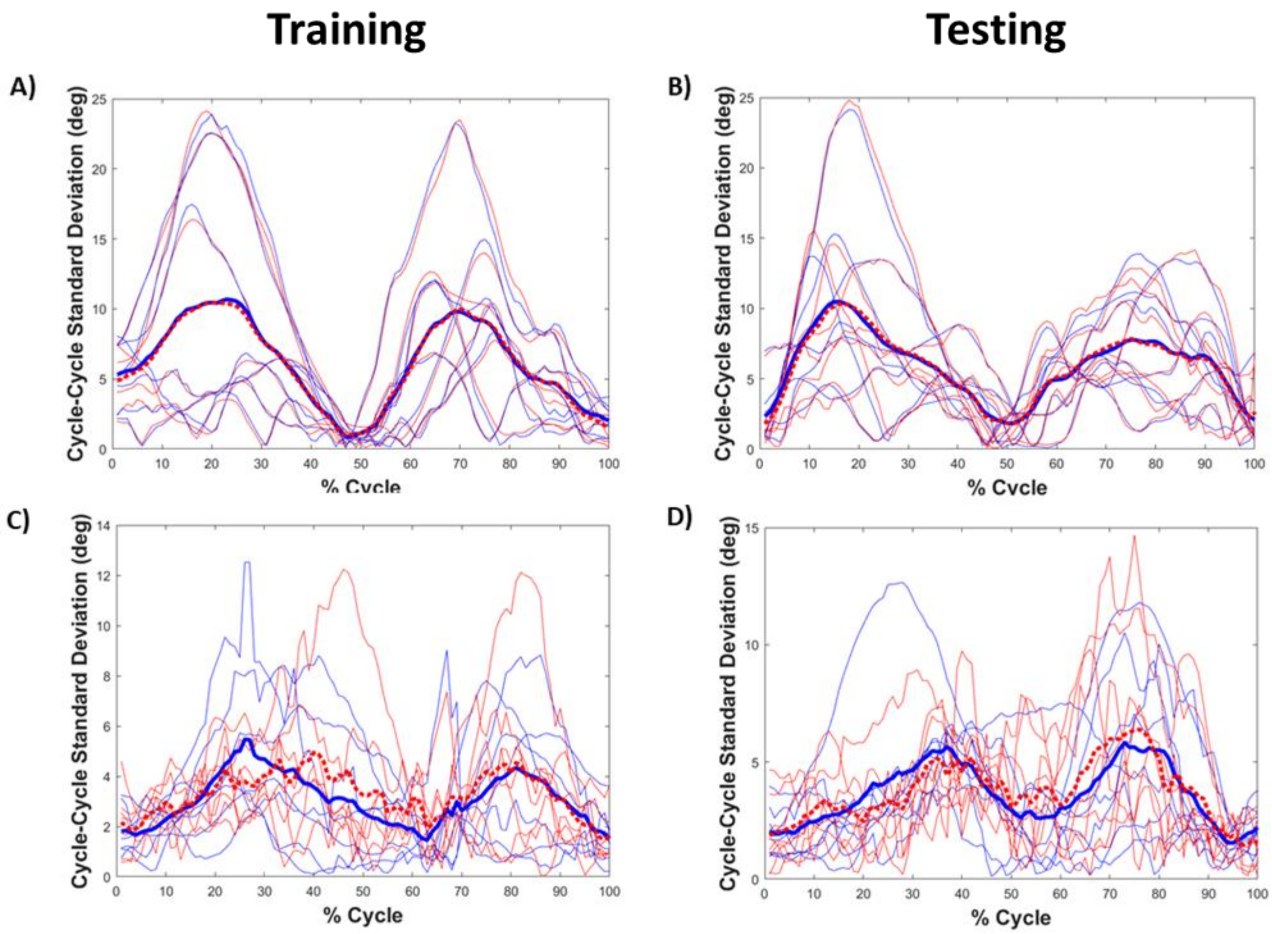

Figure 14: Cycle-to-Cycle Standard Deviation within each subject for elbow (A,B) and spine (C,D) in the train (A,C) and test (B,D) conditions

Prior to statistical comparison of ensemble cycle-to-cycle variability waveforms, the normality of residuals was again assessed using a SPM X^2 test. The results from this test are depicted in Figure 15. Suprathreshold clusters were observed for the SPM{X^2} statistic for both the elbow (Figure 15 A-C) and spine (Figure 15 D-F) cycle-to-cycle variability data. For the elbow these suprathreshold clusters were observed between 10% and 12%, 66% and 70%, and 99% to 100%. For the spine variability data suprathreshold clusters were observed between 14% and 29%, as well as between 42% and 47%. Given that the majority (i.e., > 50%) of the residuals met parametric assumptions across each ensemble of waveforms a two-way SPM ANOVA was implemented on the dataset.

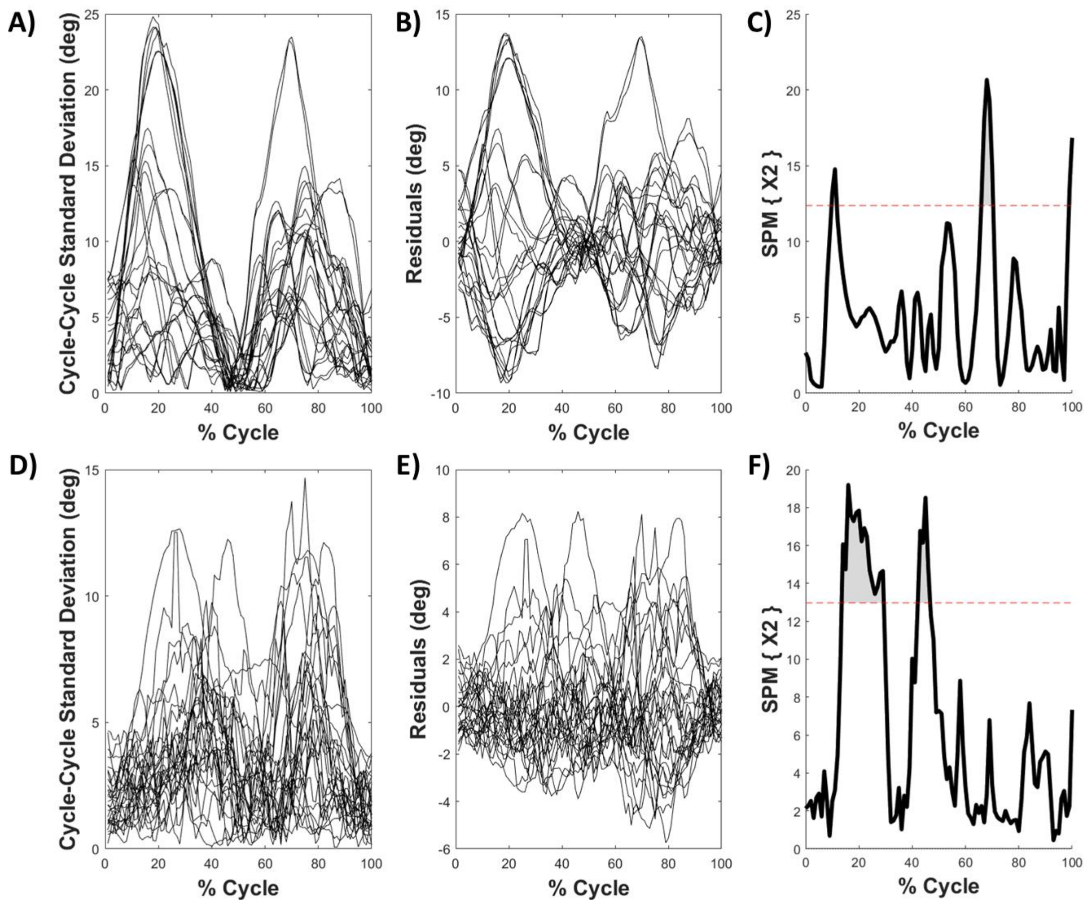

Figure 15: Visual representation of Elbow and Spine cycle-cycle standard deviations relative to % Cycle, Residual Values and SPM{X^2} Normality tests for the elbow (A-C) and spine (D-F).

The results of the two-way SPM ANOVA are depicted in Figure 16. Specifically, SPM{F} tests were completed to detect significant differences between the training vs. testing sets, capture methods (Vicon vs. DLC), as well as any potential higher order interaction effect between these independent variables in the estimation of cycle-cycle angle variability. Significant differences were only found between the Testing Set vs. the Training Set when analyzing the elbow (critical $F^* = 12.128$). Specifically, a suprathreshold cluster was observed at the beginning of the movement spanning 1-2% cycle ($p = 0.050$). The spine data showed no significant results were found when comparing training to testing set or capture methods (critical $F^* = 12.992$). There were also no significant interaction effects between the training/testing dataset and motion capture modality (i.e., DLC vs. Vicon) detected for the within participant cycle-cycle variability computed for the elbow and lumbar spine (Figure 16).

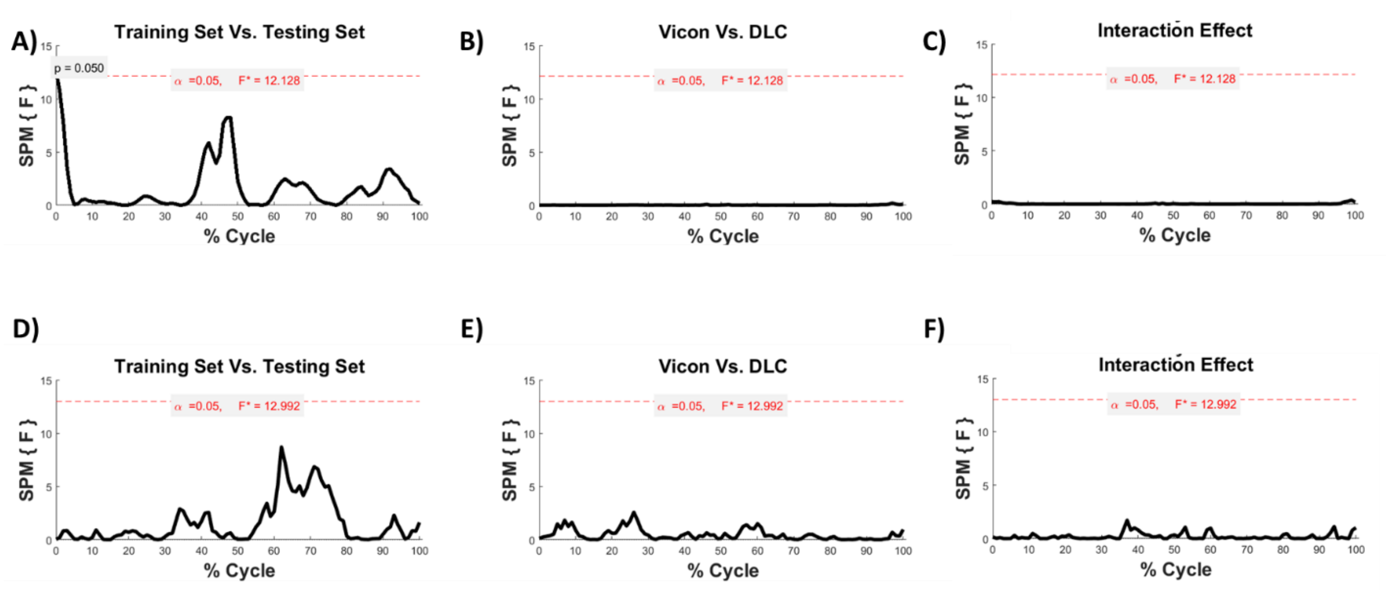

Figure 16: SPM Analysis for cycle-to-cycle variability data including Training Vs. Testing, capture methods (Vicon Vs. DLC) and the Interaction Effect for elbow (A, B, C) and Spine (D, E, F).

4.3 Supplemental Analyses of Mean Accuracy and Precision

To further understand the mean accuracy and variability of DLC with respect to the Vicon retroreflective gold standard, two additional analyses were conducted. First, differences were computed between Vicon and DLC across the duration of each elbow and spine flexion-extension cycle to infer regions of inflated error, across each dynamic flexion-extension movement. These time varying differences are depicted in Figure 17. Interestingly, the planar elbow data demonstrated increased errors during the flexion and extension phases of the elbow and spine movement, with reduced errors in neutral and fully flexed postures. The spine errors remained relatively consistent throughout the movement. When comparing the mean error in the training dataset to the testing dataset, a higher relative error was observed for the data derived from the testing dataset for both the elbow and spine.

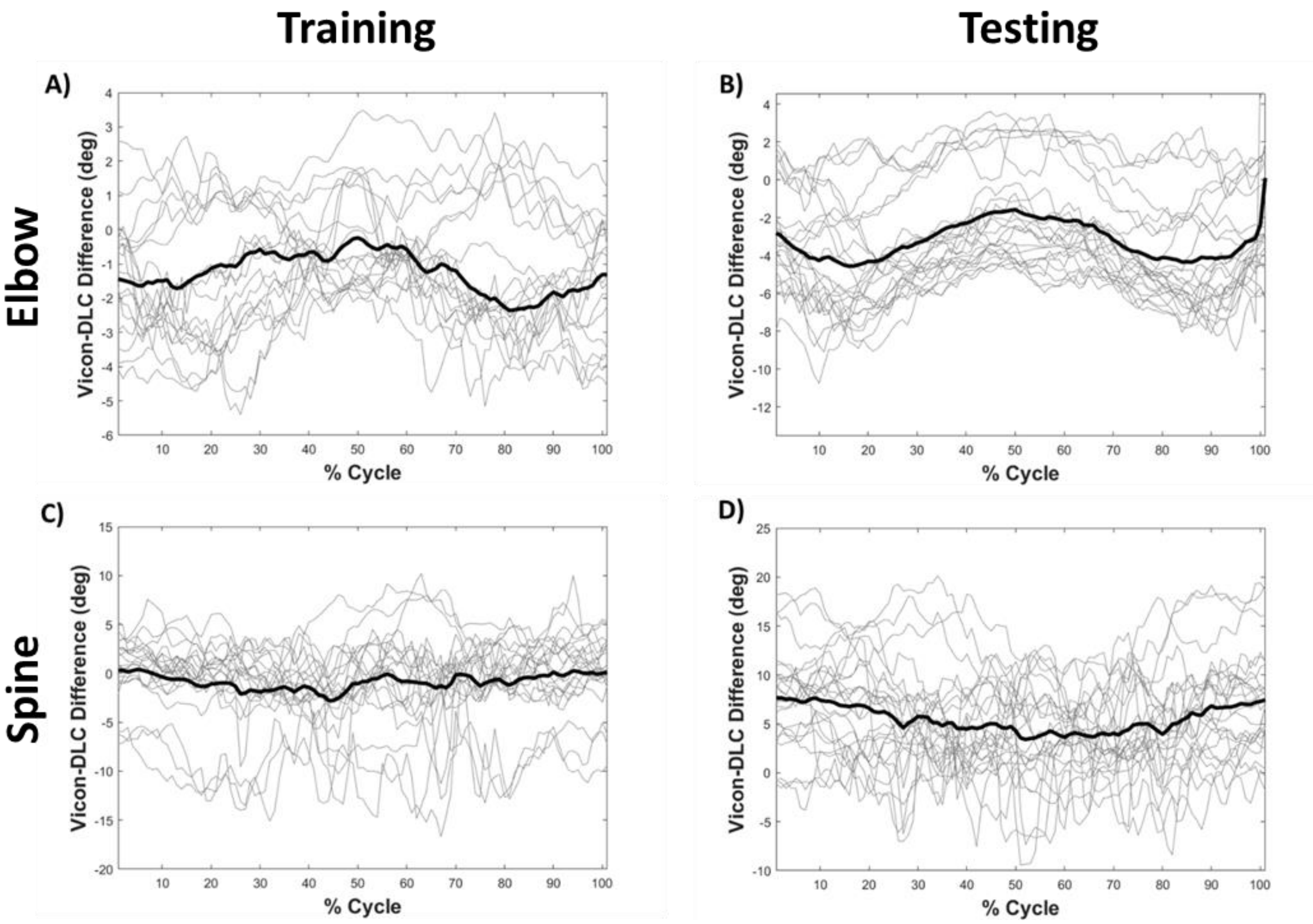

Figure 17: Ensemble Vicon-DLC error for all participants trials in elbow (A,B) and spine (C,D) as well as training (A,C) and testing (B,D) datasets.

In addition to this analysis, Bland Altman plots were generated to depict the mean bias and level of agreement between DLC and Vicon for both the spine and elbow, training, and testing datasets. These plots are depicted in Figure 18 and represent an average of all participants and cycles included in each condition. In the analysis of time-varying elbow flexion-extension data the mean bias for the training dataset was observed to be -1.25°, with the upper and lower levels agreement at -0.11° and -2.40° respectively. For the testing dataset this level of bias increased to -3.21°, with upper and lower levels of agreement at -1.23° and -5.19°. In the analysis of the time-varying spine flexion-extension data the mean bias for the training dataset was observed to be -0.85°, with the upper and lower levels agreement at 0.66° and -2.35° respectively. For the testing dataset this level of bias increased to 5.47°, with upper and lower levels of agreement at 8.10° and 2.84°.

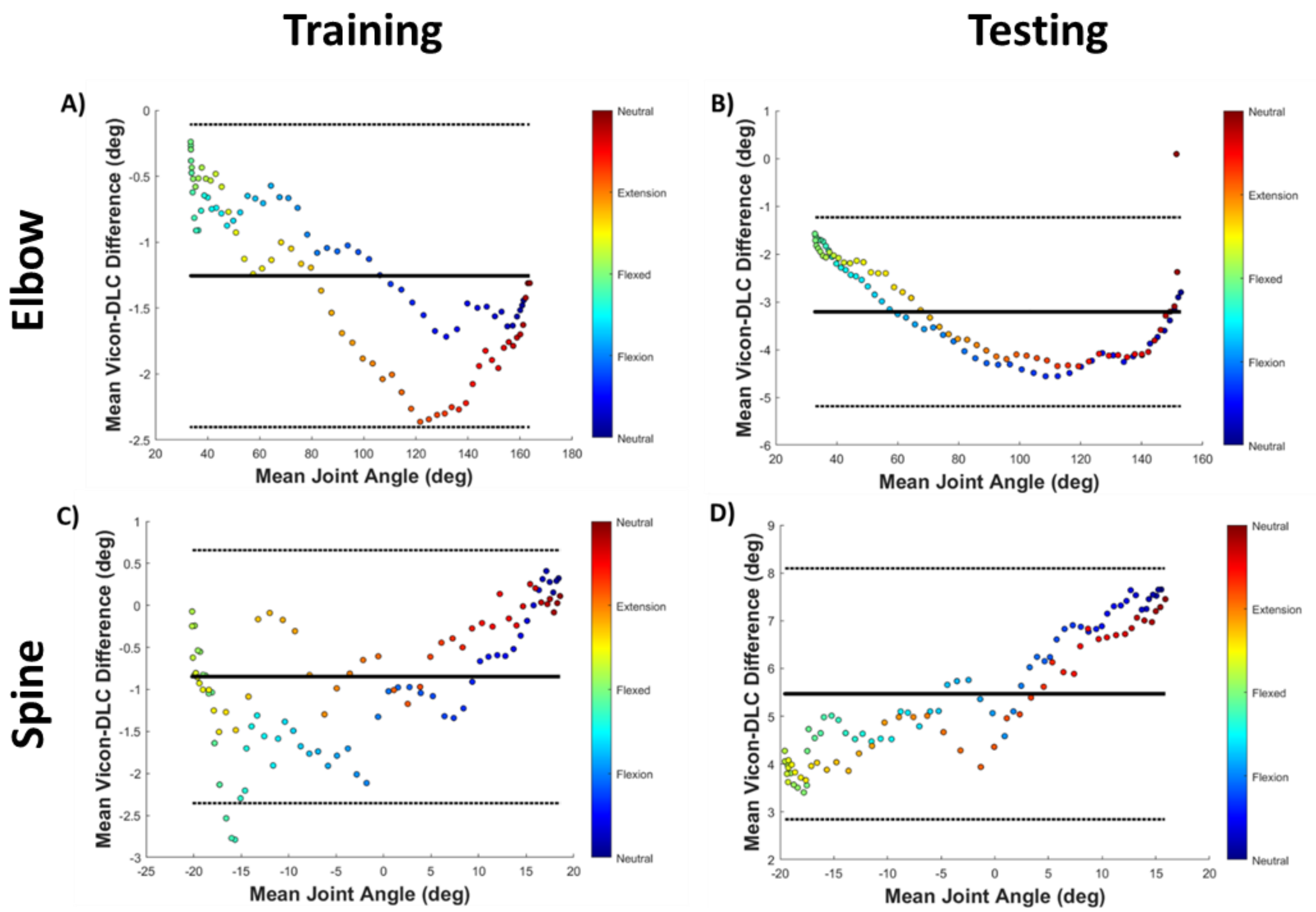

Figure 18: Bland Altman pots describing the levels of agreement between capture methods with respect to the angles produced by the elbow (A, B) and lumbar spine (C, D) in the trained (A, C) and test (B, D) conditions. Flexion-extension movement phases are colour coded, with each phase depicted on the colour bar to the right of each plot (A-D).

Finally, given the assumptions of true alignment between the Vicon global frame and the DLC camera frame, an additional analysis was completed to understand the effect of participant orientation on the degree of error computed between Vicon and DLC. Specifically, the approximate angle between the participant and the Vicon global frame were computed for each time point of every cycle. These data were then used to fit a linear regression against the computed DLC-Vicon error to infer any systematic changes in error associated with the alignment of the participant in the Vicon global frame. The results of these linear regressions are depicted in Figure 19. Statistically significant linear correlations were observed for both the elbow and spine (elbow $p < 0.001$; spine $p = 0.0272$); however, both correlations presented with weak coefficients of determination (elbow $R^2 = 0.037$; spine $R^2 = 0.003$), suggesting the lack of any systematic relationship between the transverse offset and error variables. Data interpreted from the regressions in Figure 19 show elbow data displays the least transverse offset (error) when the participants were in high flexion positions. Greatest transverse offset can be observed when the participants are approaching neutral. Regression data interpreted from the spine appears to be random across the movement phases.

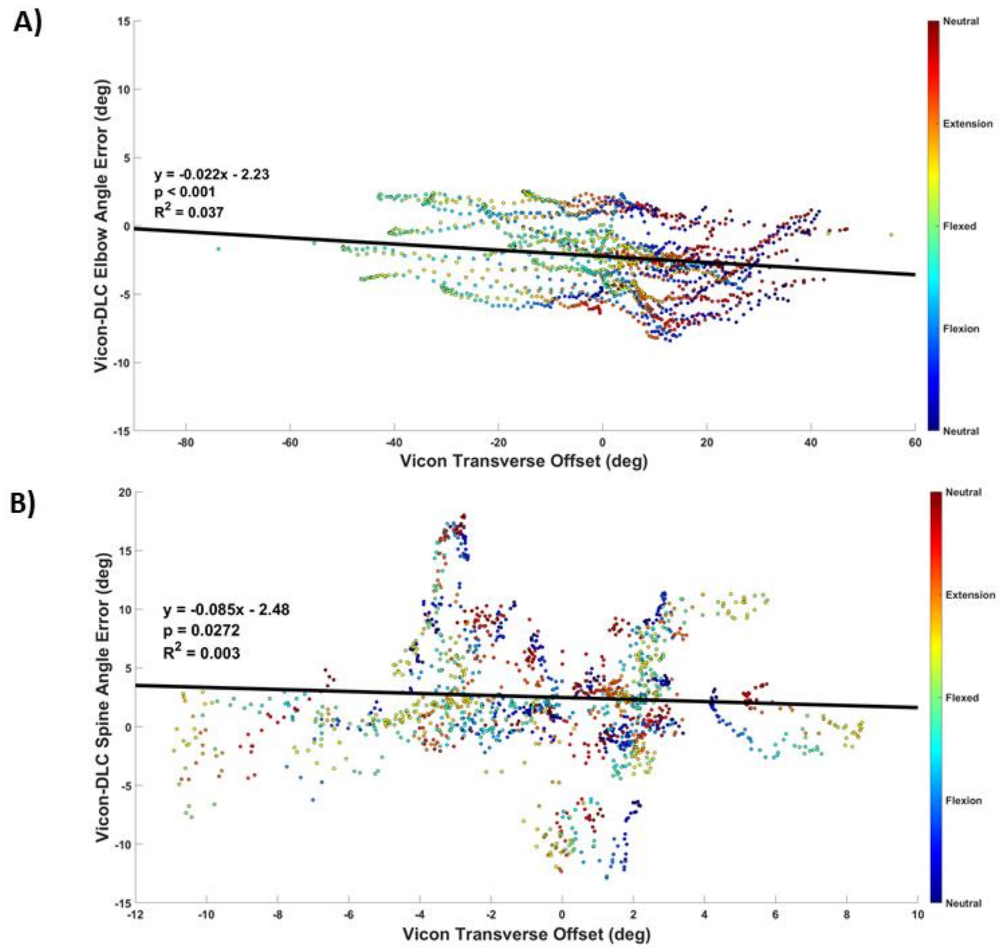

Figure 19: Computed DLC-Vicon error relative to the plotted against the rotation of each participant along the transverse axis relative to the Vicon global frame for the elbow (A) and lumbar (B) flexion-extension tasks.

CHAPTER V: DISCUSSION

The purpose of this research was to compare planar time-varying angles of the lumbar spine (complex multidimensional joint) and elbow (simple hinge joint) derived from DLC, relative to those derived from gold standard retroreflective kinematic systems (i.e., Vicon). In an ecological sense, the data from this research determined whether tracking with DLC is a good surrogate for obtaining spinal flexion data using 2D camera data in a field-based environment. Given this, it was hypothesized that DLC would be an effective method of tracking planar angles in both the lumbar spine and elbow when compared concurrently to gold standard alternatives (i.e., Vicon). As there is anatomical complexity of the lumbar spine relative to the elbow, we also hypothesized that any error, potentially associated with out of plane movement, could be minimized for the elbow relative to the gross movement of the lumbar spine. Lastly, we expected that any outcome parameters related to joint angular displacement or angular displacement variability would not differ when compared statistically between DLC and Vicon. In general, the findings of this work support these hypotheses. Specifically, no notable main effect difference was identified between DLC and Vicon in terms of overall accuracy (Figure 13) or cycle-to-cycle variability (Figure 16). In addition to this, there was no statistically significant difference in the performance of DLC relative to Vicon when assessing the training vs. testing datasets (Figures 13 and 16). Finally, the findings presented here appear to be robust to any potential error associated with misalignment between the body segment being analyzed and the true Vicon global sagittal plane (Figure 19). Collectively these findings suggest that video data analyzed using a DLC framework is a viable alternative to conventional gold standard approaches (i.e., Vicon) in the assessment of planar lumbar spine and elbow time-varying relative joint angles. There are, however, some considerations in the quantification of planar angles using video data and DLC which will be discussed in the subsequent sections of this thesis.

5.1 DeepLabCut vs. Vicon Accuracy

To statistically evaluate any differences in the planar joint angles evaluated using DLC and Vicon, an SPM approach was taken. This approach identifies specific time-bins (i.e., suprathreshold clusters) where statistically significant differences exist between groups of interest. Once confirming the normality of time-series residuals (Figure 12) and implementing a two-way SPM ANOVA onto the dataset of time-varying angles (Figure 13), suprathreshold clusters were detected (Figure 13 A), representing a significant difference between the training and testing sets for the time-varying elbow data. Despite this, no significant differences were detected between motion capture modalities (i.e., DLC vs. Vicon), or for any higher-order interaction effects (i.e., dataset*modality) for either the spine or elbow (Figure 13 B, C). These findings suggest that although there may have been systematic differences in the elbow data included within the testing and training sets, the relative accuracy of DLC vs. Vicon was not statistically different, nor was this relative accuracy affected by the analysis of training vs. testing datasets. Overall, this demonstrates for the entire Max-fROM movement, both capture methods (DLC and Vicon) showed great agreement when tracking the planar flexion-extension movement of the elbow and spine.

In addition to the statistical comparisons noted above, an additional aim was taken to quantify the relative bias, and levels of agreement between DLC and Vicon using time-varying relative error plots (Figure 17), and Bland-Altman analysis (Figure 18). In the assessment of time-varying error, ensemble and mean relative error waveforms were generated, which clearly depict an improvement in accuracy for the training set (Figure 17 A, C) relative to the testing set (Figure B, D). Further, in the appraisal of the mean error waveforms, it is clear that the relative error between DLC and Vicon is affected by the relative elbow posture being analyzed (i.e., Figures 17 A, B); however, remains relatively consistent throughout a flexion-extension movement cycle for time varying spine flexion extension data (Figures 17 C, D). These findings suggest that relative error is reduced between DLC and Vicon in the assessment of time-varying elbow angles when a participant is positioned in either a fully flexed (i.e., 0% cycle, 100% cycle) or fully extended (i.e., 50% cycle) posture. Bland-Altman analyses corroborated these relationships and provided estimates for mean bias for each joint for both the training and resting datasets (Figure 17). Specifically, the Bland-Altman plots depicting the relative error for the elbow data (Figure 17 A, B) take a ‘U’ shape suggesting improvements in accuracy (i.e., less DLC undershooting) in flexed and extended postures relative to intermediate ones. Further, those presented for time-varying spine angle data take a linear form suggesting a mix of errors throughout a flexion-extension movement. The majority of all measurements fell within two standard deviations (SDs) of the mean, representing the upper and lower levels of agreement, between DLC and Vicon in the in the sagittal plane Max-fROM testing for both spine and elbow. When comparing the relative bias between the training and testing datasets for both joints, it is also clear that relative error was improved when assessing training data rather than testing data. Specifically, the relative bias for elbow training data was -1.25^{o}, and was -3.21^{o} for the testing data. Further the relative bias for the spine training data was -0.85^{o}, and was 8.10^{o} for the testing data. For the elbow data all biases were consistently undershooting Vicon angle estimates; however, those for the spine included both under and over-estimation errors. On average, the performance of DLC was improved in the assessment of time-varying elbow angle data with respect to those computed for the lumbar spine. Collectively, these findings constitute a decrease in performance in the analysis of new data for the DLC neural network. Although these errors may not be statistically significant (based on SPM analyses, noted above), further discussion is warranted regarding whether these errors are acceptable in a clinical or performance related setting. According to a systematic review performed by Mcginley et al. (2009) in gait kinematics sensor error between levels between two and five degrees was deemed reasonable for clinical interpretation. As Vicon is the gold standard which DLC is attempting to match, DLC's bias remained within five degrees except in the evaluation of the spine testing dataset (Figure 18 D). Therefore, it is likely that DLC is an acceptable alternative in the analysis of both time-varying elbow and spine flexion-extension data in a clinical setting. A meta-analysis performed by Laird (2014) overviewed 17 ROM studies, this ROM data resulted in an average LBP group 41.582˚ and non-LBP 50.611˚. This represents a mean difference of approximately nine degrees in flexion ROM between those affected with LBP relative to those unaffected. The results of the current study suggest that the accuracy of the spine ROM data, evaluated using DLC is suitable to detect such a change when derived from the training dataset; however, those derived from the testing dataset may have insufficient accuracy to detect such a clinically meaningful change. Future work will be needed to determine whether additional data is necessary to improve the accuracy of a DLC model to derive planar angles from new data, unused in the training of a model.

To compliment the analyses above, and to understand the effect of participant orientation on the relative error between DLC and Vicon, an additional linear analyses was completed to quantify the relative impact of participant global orientation (i.e., misalignment with respect to the Vicon global frame), on the level of accuracy between DLC and Vicon. For both the elbow ($p < 0.0001$) and spine ($p = 0.0272$), statistically significant correlations emerged (Figure 19), suggesting that the data trends were not purely random. Specifically, in both cases there is a weak positive relationship between the computed Vicon transverse misalignment and the relative error between DLC and Vicon. This suggests that as a person rotates toward, or away from the idealised Vicon sagittal plane DLC-Vicon accuracy is weakly affected. Through interpretation of each trendline it can be noted that the relative error at zero degrees was 1.5 and 4.0 degrees for the elbow and lumbar spine, respectively. These values mirror the bias values presented in the Bland-Altman plots (Figure 18), suggesting good alignment between the human participants and the Vicon global sagittal plane, on average. Nevertheless, improvements in accuracy can be obtained with true alignment between the DLC camera plane, and the Vicon global sagittal plane. Of note, a larger range of Vicon transverse plane misalignment values were observed for the elbow in comparison to the spine. Further the findings for the elbow suggest that errors are largest when a participant approaches a neutral (fully extended) posture, whereas the errors for the lumbar spine did not demonstrate any systematic pattern across each flexion-extension movement.

Although the findings noted above are promising, there are possible reasons for reduced accuracy within the movement conditions while being tracked by DLC. One of the largest reasons for reduced concurrent accuracy between DLC and Vicon has been quantified above. Specifically, misalignment of the participant with respect to the Vicon global frame could result in inaccurate planar data. This accounts for any rotation in the transverse plane where markers are not directly in a perpendicular alignment with the vision of the Vicon Vue camera. This could be caused by lumbar fin markers slipping or rotating around the body in the transverse plane with movement. This transverse offset could also be caused by the participant rotating their trunk or foot placement relative to their initial placement. As depicted in Figure 19, there are both positive and negative data points associated with the elbow and spine. These points also show a low R^2 value for both elbow ($R^2 = 0.022$) and spine ($R^2 = 0.002$). This means that these values show low correlation and are not likely to influence agreement between Vicon and DLC. In addition to any errors associated with misalignment, image blur is another potential issue associated with reduced accuracy of DLC. Specifically, image blur could be caused by acceleration of the joint moving through the frame. This segment acceleration coupled with a lower quality resolution of video may result in poor tracking quality of DLC and this could partially represent why tracking appears in intermediate elbow flexion extension postures when evaluating time varying ensemble error (Figure 17). Another potential source of error which may influence the relative accuracy of DLC at different body postures is the number of training frames included to train the neural network to evaluate such postures. Participants tended to pause at their end ranges of motion for both elbow and spine, resulting in a disproportionate number of video frames representing these postures. Although, DLC implements an unsupervised approach (i.e., k-means) to optimize the selection of diverse body postures for the inclusion into the training dataset, it is possible that this training dataset was biased to evaluate postures associated with max flexion and extension of the elbow joint. This can explain the better agreement between Vicon and DLC and the end ranges of motion. Finally, an additional source of error for DLC when tracking planar angles are the changes in demographic between the training and testing group. This may be due to the physical or visible differences between participants. These differences could be height, anthropometrics, hair length, skin tone, or even the style of clothing worn within each group. These factors could result in reduced accuracy (especially for the participants that make up the testing set) as DLC has only been trained on a portion of the participants. One example of such differences included within the current analyses would be the statistically significant differences noted between the testing and training datasets for the acquired time-varying planar elbow data (Figure 13A).

5.2 DeepLabCut vs. Vicon Cycle-Cycle Variability

Cycle-to-Cycle variability was estimated to evaluate the precision of DLC with respect to the Vicon gold standard when tracking the planar angles across multiple flexion-extension movements. Significant differences in precision are demonstrated in Figure 16. Specifically, two-way SPM{F} ANOVA tests were completed to detect significant differences between the training vs. testing sets, capture modalities (Vicon vs. DLC), as well as any potential higher order interaction effect between these independent variables. Significant differences were only found between the Testing set vs. the Training Set when analyzing the elbow (critical F^* = 12.128) at the beginning (1-2%) of the cycle, where a single suprathreshold cluster was detected. No other significant differences were detected between motion capture modalities (i.e., DLC vs. Vicon), or for any higher-order interaction effects (i.e., dataset*modality) for either the spine or elbow (Figure 16 B, C). These findings suggest that there again, may have been systematic differences in the elbow flexion-extension cycle-to-cycle variability data included within the testing and training sets, despite this the relative precision of DLC vs. Vicon was not statistically different, nor was this relative precision affected by the analysis of training vs. testing datasets for the lumbar spine.

In addition to the assessment of cycle-to-cycle standard deviation as an estimate of relative precision, the variability in error (i.e., accuracy) estimates can also provide an estimate of precision when inspected across all cycles/participants. These estimates of variability across all participants can be observed through the inspection of Figures 17-19. First, Figure 17 depicts the relative error between DLC and Vicon computed across all time-series data for the elbow (A, B) and spine (C, D). By inspecting the spread of these data, it is possible to infer the relative variability (i.e., precision across all cycles and participants). Interestingly, between elbow training and testing datasets there is a much larger spread between the grey lines, representing a decreased precision in the evaluation of the testing dataset. The same phenomenon appears to exist for the spine dataset. Additionally, the relative spread of the data appear to be larger for those acquired for the lumbar spine relative to those acquired for the elbow. Next, Figure 18 depicts variability across all cycles/participants through the upper and lower levels of agreement. Specifically, those data with higher precision can be inferred to have a smaller difference in upper and lower levels of agreement. In both the elbow and spine movement conditions, the difference between upper and lower LOA increased (i.e., became worse) in testing sets relative to training sets. This means that there was a decrease in precision in all testing sets. Finally, when inspecting Figure 19, one can loosely interpret the relative precision of DLC by assessing the spread of the data along the y-axes. When inspecting Figure 19, it is clear there is a wider spread of data along the y-axis for data obtained from the lumbar spine (Figure 19 B) relative to those obtained from the elbow (Figure 19 A), representing an increased precision (i.e., repeatability) of errors for movement of the elbow.

In general, many potential factors affecting DLC precision (i.e., DLC-DLC estimates between cycles/participants) will mirror those affecting DLC accuracy (i.e., DLC compared against Vicon). Realistically, many errors in precision may be obtained from unreliable estimations completed by the DLC algorithm between difference cycles or participants. The DLC algorithm’s ability to correctly match the Vicon physical marker is dependent on some specific factors, which if inconsistent between cycles/participants may affect the variability estimates computed with the current work. First, postural changes between cycles could cause DLC to "guess" where a virtual marker should be placed. The differences between cycles could primarily be caused by postural changes in alignment of an individual's body segments. These changes in posture throughout movement cycles may result in misalignment of each body segment with respect to the camera frame, requiring DLC to extrapolate data to interpret where the physical marker would be placed on the participant, or evaluating a marker with reduced confidence. This is because the Vicon Vue camera may not be trained to account for this misalignment between the markers (especially for the testing group participants). Second, movement speed, if different between cycles and participants, may result in decreased DLC precision with respect to Vicon. Specifically, in addition to any errors associated with misalignment, image blur is another potential issue associated with reduced precision of DLC. As previously mentioned, image blur could be caused by joint acceleration through the frame. This blur could reduce the visibility of the markers to DLC and require it to evaluate a virtual marker with lowered confidence. This reduced precision due to motion blur may also be more likely to appear between end ranges of motion, where movement velocities are highest. This could be further augmented by a lack of training frames for such postures, as previously described. The final factor that may influence repeatability and precision in this study is the potential movements of objects (i.e., rigid bodies, clothing, hair, etc…) on participants between repeated cycles of the same movement. Such movement may impede the ability of DLC to accurately evaluate any points of interest between cycles. For example, if a participant's hair or shirt falls out of a tie or slips out of the harness it may become baggy and fall or swing in front of markers during flexion cycles for both elbow and spine. In addition to maker blockage, these 'environmental' changes may be otherwise unknown to DLC thus reducing tracking precision.

5.3 Limitations

The current work does not come without any limitations. As previously mentioned, the current work assumes that there is pure alignment between the camera frame and the Vicon global (i.e., sagittal) frame when measuring planar angles. Such (mis)alignment is difficult to control; however, could potentially reduce agreement between Vicon and DLC this includes any moment of the Vicon motion capture markers in the non primary (transverse) axis. Figure 19 demonstrates that there may be some weak influence due to this misalignment in the data; however, the effects are small in this application. Second, this research used a relatively small and homogenous sample size. A convenience sample of university-aged participants were used for the current study. Results may differ given a wider participant base (including multiple diverse demographics). Specifically, this would further strengthen the results by allowing DLC to train itself on a larger group of participants with more diverse physical features may allow the program (DLC) to be better generalized among a larger population.

5.4 Future Work

The aim of this work was to analyze the accuracy of DLC in the estimation of planar body kinematics under idealized scenarios (i.e., proper lighting, clearly visible markers, etc.). Thus, this project analyzed 2D planar angles of the elbow and lumbar spine is a controlled lab setting and many precautions were taken to ensure that DLC was given the best possible case scenario to track the reflective Vicon markers. For future research it may be valuable to challenge the ability of DLC to track planar angles in non-idealized scenarios, which may potentially have additional ecological relevance (i.e., clinical or sport related settings). Environmental challenges to apply to DLC include lighting changes and different cameras/backgrounds in training vs. testing conditions. Another factor that may influence DLC includes the diversity of participants that it is trained and tested on. Through changing these factors, it will test the robustness of DLC when applied to extracting planar angles under non-idealized conditions. There is additional merit to evaluate the ability of DLC to estimate relative planar joint angles in body segments moving outside of the sagittal plane. Specifically, another way to build on this research is to incorporate the use of DLC tracking for motions in the frontal and transverse planes. To evaluate lumbar spine lateral bending with the Vicon system, participants would be required to wear a new marker set. This could include standard Vicon reflective markers on vertebrae of interest. To evaluate twisting in 2D there are multiple approaches. Using a segmented belt marker system or top-down view of the subject may be effective for evaluating movement such as twisting in the transverse plane. In addition, to further analyzing the remaining anatomical planes independently there is also merit to expand the current analyses to 3D using multiple camera inputs. DLC is a highly capable platform with the ability to add multiple 2D cameras for 3D video analysis (Nath et al. 2019). The use of multiple cameras facilitates the acquisition of multiple camera views which can be triangulated to estimate 3D coordinates. To the researcher's knowledge, no 3D validation testing has taken place on a human model using and optoelectronic system along with DLC (especially when evaluating kinematics of the spine). This creates another avenue to expand on the current research.

Upon completion of the further validation work described above, there is a further need to understand the relative accuracy of computer vision-based approaches in the estimation of body kinematics without the use of kinematic markers. Specifically, one of the largest benefits of DLC is its ability to be used without physical markers. The ability to arbitrarily create both an accurate and precise *virtual* markerset, based on visible anatomical landmarks, would be an asset when collecting and analysing kinematic data. As this study was the first to evaluate lumbar kinematics with DLC using the T12 and S1 using a custom markerset, it may be beneficial for researchers to further reduce intervention when observing these movements through the removal of this equipment. This lack of equipment could reduce the chance of artificial stimulus and altered kinematics of the participants (Mundermann et al. 2006). This unimpeded natural movement may be more natural and therefore ecologically relevant when applied to a clinical setting. This would also allow patients to send videos to clinicians to be remotely assessed without the anatomical domain knowledge required to place a markerset on their bodies. Finally, there is an eventual need to expand the validation of computer vision based kinematic approaches (such as DLC) to the estimation of higher-order measures of movement coordination. These may include measures such as a Lyapunov Exponent (Beaudette et al., 2015) to infer dynamic stability or estimates of continuous relative phase to infer segment/joint couplings (Beaudette et al., 2019).

5.5 Conclusions

The results of the study suggest that DLC is effective in terms of accuracy and precision (relative to a retroreflective Vicon gold standard) when tracking planar angles in the sagittal plane for the elbow and lumbar spine. Overall, DLC was clinically acceptable in terms of accuracy when analyzing planar elbow and lumbar spine flexion in the sagittal plane. Further improvements in accuracy can be obtained by pure alignment between DLC and Vicon 2D frames. This could be made stricter if a researcher was constantly monitoring transverse offset while participants were completing the test or using a guide to restrict joint movement to one plane during the test. Future studies will investigate different movement sequences in the frontal and transverse planes, utilizing DLC’s 3D capability to analyze kinematics, while also utilizing DLC as a completely markerless system and expanding DLC’s validation to include other measures of movement (i.e., dynamic stability and movement coordination).

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APPENDIX A – GENERAL HEALTH HISTORY QUESTIONNAIRE

SPINE BIOMECHANICS
& NEUROMUSCULAR CONTROL LABORATORY

Generic Health History Form

Age: Sex: Height: Weight:

1. Have you ever experienced pain in the back that has caused you to miss school, work or any regular activity?

   □Yes (If Yes, please describe) □No
   Date:

2. Have you ever sought medical treatment (physician, chiropractor, physiotherapist) relating to your back?

   □Yes (If Yes, please describe) □No
   Date:

3. Have you ever experienced skin sensitivity or an allergic reaction to adhesives or ink such as medical tape, Band aids, medical electrodes or washable markers?

   □Yes (If Yes, please describe) □No

4. Have you ever sought medical treatment relating to a skin condition?

   □Yes (If Yes, please describe) □No
   Date:

5. Do you regularly engage in any type of physical activity?

   □Yes (If Yes, please describe) □No

6. Have you ever been classified as having a musculoskeletal (e.g. Parkinson's Disease or Cerebral Palsy) or Neurological (e.g. Diabetic Neuropathy or concussion) disorder which may affect your balance or movement?

   □Yes (If Yes, please describe) □No

   Date:

7. Have you ever been classified as having an auditory (e.g., inner ear disorder, vertigo, upper respiratory infection, etc.) disorder which may affect your balance or movement?

   □Yes (If Yes, please describe) □No

   Date:

8. Have you ever experienced an injury, for which you sought medical treatment, to your lower limb (e.g ankle, knee or hip)?

   □Yes (If Yes, please describe) □No

   Date:

APPENDIX B – INFORMED CONSENT FORM

Informed Consent Form

Date: September 2020

Project Title: Assessing the Utility of a Markerless Motion Capture Alternative in the Assessment of Spine Movement Kinematics

Principal Investigator:

Dr. Shawn Beaudette

Assistant Professor

Brock University

Ph: 905-688-5550 x6687

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Principal Student Investigator:

Mr. Paul Goncharow

Graduate (MSc) Student

Brock University

Ph: 905-688-5550 x5623

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<u>INVITATION</u>

You are invited to participate a research study assessing the precision, reliability and validity of a novel markerless motion capture algorithm. During this study we will be analyzing body movements. The purpose of this study is to compare the markerless system against a gold standard (Vicon), in the assessment of dynamic spine movement kinematics.

To be <u>eligible</u> for this study, you must:

- be between 18 and 30 years old
- be in good general health
- have not experienced low back pain within the past 3 months
- be free of any neurological (e.g., concussion within the past six months, Parkinson's disease, Amyotrophic Lateral Sclerosis, Multiple Sclerosis, vertigo, etc.), orthopedic (e.g., recent fracture, osteoporosis, osteoarthritis, etc.), muscular (e.g., recent sprain, strain, or tendonitis, muscular dystrophy, etc.), or hearing injuries or disorders and current upper respiratory infection that may interfere with your balance and mobility
- you must not have any known allergies to rubbing alcohol or adhesives

Do you think you are eligible for this study? _______ (Please indicate YES or NO)

(If you are unsure of your eligibility, please ask the researcher for any clarification)

The research is a single-site project. There are no conflicts of interest on the part of the researchers or their institution.

WHAT'S INVOLVED

As a participant, you will be asked to perform the following tasks during one (2-hour) testing session at the Spine Biomechanics and Neuromuscular Control Laboratory (WH23) at Brock University. Throughout each experiment, you will be required to wear comfortable athletic shorts and athletic shoes. Male participants will be asked to be shirtless and females will be asked to wear a sports bra (to facilitate the placement of experimental equipment).

Familiarity Period (approximate duration: 5 minutes)

During the study visit, elbow flexion-extension, spine flexion-extension and lateral bending will be collected using video and 3D motion capture equipment. To track specific body landmarks, specific regions of your body will be designated with a reflective sphere, or washable marker (Figure 1). To ensure that you are familiar each of these data streams, you will practice movements using a single reflective sphere placed on your back.

Skin Marking and Experimental Set-up (approximate duration: 15 minutes):

During this stage of the experiment you will be asked to stand. While standing, your skin will be cleansed with rubbing alcohol to allow for the placement of experimental equipment.

For this experiment, two types of experimental markers will be placed at specific locations on your body. 3D motion capture pearls will be placed on your skin using adhesive tape to track the 3D location of your body segments. Four marks will also be made on your back with a washable marker. The marker dots will be placed over specific vertebrae (bones) to designate their location. The location of each pearl, and marker dot can be seen in the picture below. You will also be required to wear two belts with reflective markers around your abdomen and waist in specific locations.

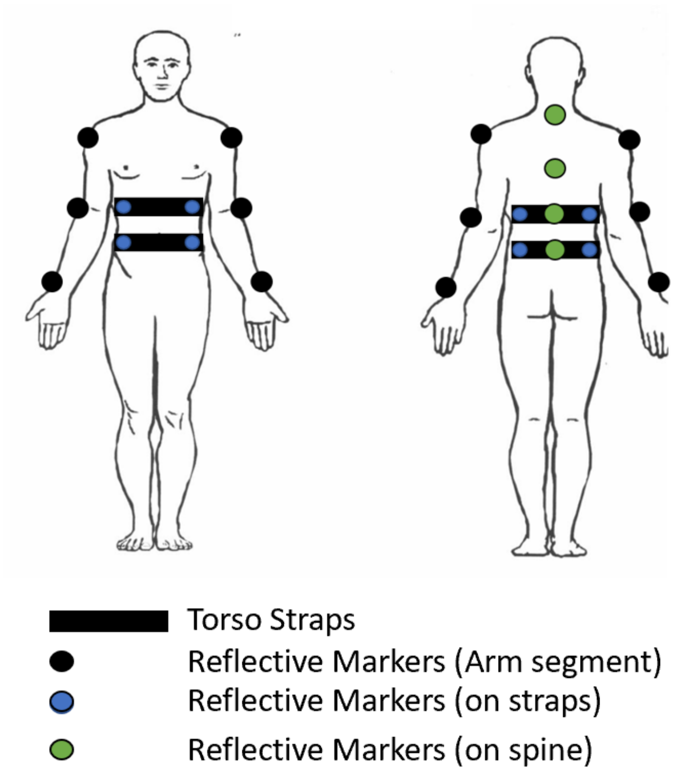

Figure 1. Motion Capture Marker Placement

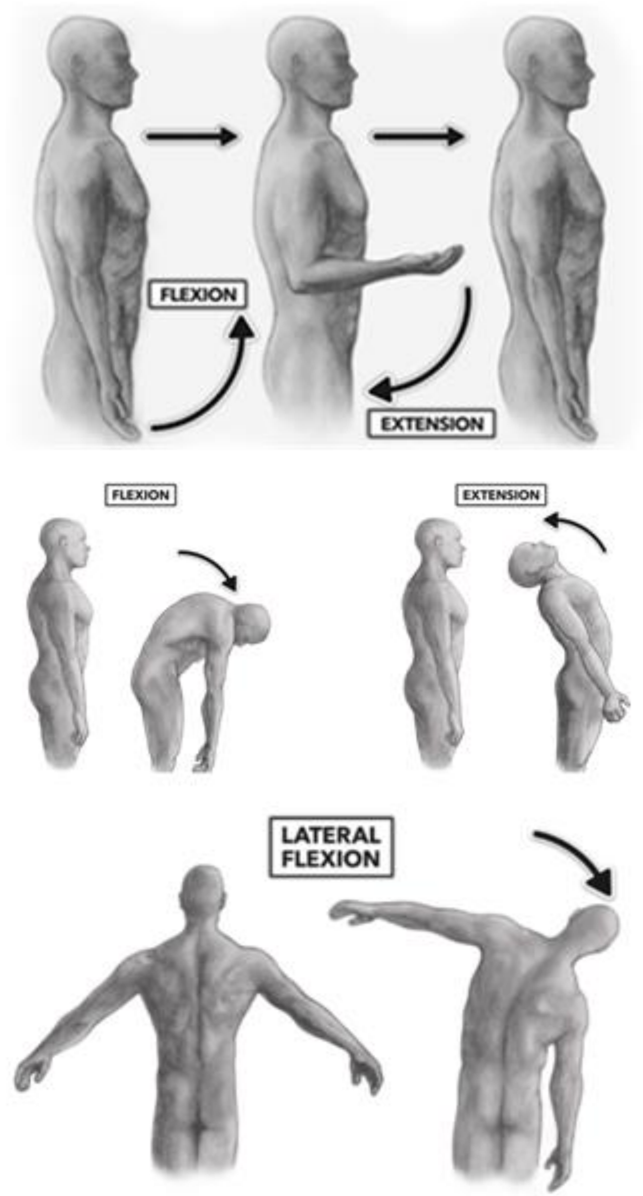

Figure 2. Pictures demonstrating the ROM movements.

<u>Movement Trials (approximate duration: 60 minutes):</u>

Next, you will be required to stand in a specific area of the lab. During this period, you will be asked to stand up straight with your arms at your sides. The researcher will tell you when to complete the bending and elbow flexion protocol.

A) **Elbow Flexion-Extension (Elbow-FE)**: You will be asked to complete a simulated supinated (palms up) barbell biceps curl with a light (~10 lb) load. You will be asked to begin in a fully extended elbow position, reach a fully flexed position, and return to the initial fully extended starting position.

B) **Spine Flexion-Extension (Spine-FE)**: You will be asked to complete a forward flexion movement. You will begin each movement in a standing neutral posture. From this posture, you will bend your spine forward as far as possible before returning to the initial neutral standing position.

C) **Spine Lateral Bending (Spine-LB)**: You will be asked to complete a bilateral bending movement. You will begin each movement by standing in a neutral posture. From this posture you will bend your spine in the right and left directions by sliding your hand along your thigh until you reach your full range of motion in either direction. Once complete, you will return to the initial starting position.

Equipment Removal (~ 5 minutes in duration)

Upon completion of all the trials above, all equipment will be removed from your body. Your skin will be cleansed using rubbing alcohol to remove any adhesive or washable marker.

POTENTIAL BENEFITS AND RISKS

The data collected from the study has no direct benefit to you as a participant. However, you will have the opportunity to learn more about spine biomechanics and motion capture research through your involvement in the experiment. More broadly, the findings from this study will contribute to our understanding of how motion capture alternatives can impact on the progression of motion capture research.

There exists a small risk of irritation/itching from the preparation and placement of the 3D motion capture pearls (i.e. stickers). This risk will be managed through use of hypoallergenic materials as much as possible. Please alert the investigator if you feel any pain or discomfort during or after the experiment. You will also be informed in advance of any materials that will contact your skin. Finally, it is possible that you may feel self-conscious while participating in this study when shirtless (males), or while wearing a sports-bra (females). To accommodate this, all experiments will be completed behind closed doors. If desired, you can request to have a researcher of the same-sex apply the required equipment (i.e. Marker Points and 3D motion capture pearls).

CONFIDENTIALITY

All information that you provide is considered confidential. Your name will not be included or, in any other way, associated with the data presented in study reports. You will be assigned a code number so that your name cannot be connected to the data collected. Furthermore, because our interest is in the average responses of the entire group of participants, you will not be identified individually in any way in written reports of this research. Data collected during this study will be stored in a locked cabinet and on password-protected computers in the Spine Biomechanics and Neuromuscular Control Laboratory at Brock University (WH 23). Only the investigators of this study will have access to the data. With your additional consent (below) data will be maintained indefinitely in a study database to support future secondary uses. Otherwise, data will be kept for five years following the publication of the study, after which time the data will be destroyed.

SECONDARY DATA USES

The investigators are interested in potential secondary uses for the study data. Through these secondary uses, current and future trainees studying within the Spine Biomechanics and Neuromuscular Control Laboratory will have access to your study data. If you elect to allow for secondary uses of the study data (second signature line at the end of this form) your study data will be maintained indefinitely under a participant specific numerical identifying code. Identifying information (i.e. your name) will also be maintained indefinitely within a single electronic form, accessible by only the principal investigator. This form will be used to link your name to a specific numerical participant identifier, which will be used to file the remainder of the data gathered through this study.

VOLUNTARY PARTICIPATION

Participation in this study is voluntary. You may choose not to perform any or all the trials included in the study. You may also withdraw from this study at any time during the experiment and without penalty by informing the researchers of this study. Your participation or your withdrawal will not affect your current or future standing at Brock University. If you withdraw from the study, you will have the option for your computerized data records to be deleted, and physical records to be destroyed.

PUBLICATION OF RESULTS

Results of this study may be published in professional journals and presented at conferences. General feedback (i.e., research findings) about this study will be available at the conclusion of the research project. Should you wish to receive a summary about the study results, please complete the attached "Request for Summary of Results" form. Please note that individual feedback will not be available because results are analyzed as part of a larger data set.

CONTACT INFORMATION AND ETHICS CLEARANCE

If you have any questions about this study or require further information, please contact the Principal Investigator using the contact information provided on the first page. You do not waive any legal rights by agreeing to take part in this study. This project has been reviewed by the Brock University Research Ethics Board for compliance with federal guidelines for research involving human participants. If you have questions regarding your rights and welfare as a research participant in this study (REB 20-086), please contact:

Office of Research Ethics — Telephone: (905) 688-5550 ext. 3035

Brock University — E-mail: reb@brocku.ca

INFORMED CONSENT

I agree to participate in the study described above. I have made this decision based on the information I have read in the Informed Consent Letter. I have had the opportunity to receive any additional details I wanted about the study and understand that I may ask questions in the future. I understand that I may withdraw with this consent at any time.

Name: ________________________________ (please print)

Signature: __________________________________ Date: ___________

SECONDARY DATA USES

I agree to allow for any secondary uses of my study data. This includes the indefinite retention of the data gathered through this study, and the maintenance of a digital form linking my name to my numerical participant identifier (only accessible by the Principal Investigator). I have made this decision based on the information I have read in the Informed-Consent Letter. I have had the opportunity to receive any additional details I wanted about secondary data uses and understand that I may ask questions in the future. I understand that I may withdraw with this consent at any time.

Name: ________________________________ (please print)

Signature: __________________________________ Date: ___________

Thank you for your assistance in this project. Please keep a copy of this form for your records!

Department of Kinesiology, Brock University Request for Summary of Results

April 2020

Title of Study: Assessing The Utility of a Markerless Motion Capture Alternative in The Assessment of Spine Movement Kinematics

Principal Investigator:

Dr. Shawn Beaudette, Assistant Professor, Department of Kinesiology, Brock University

Principal Student Investigators:

Mr. Paul Goncharow, Masters Student, Department of Kinesiology, Brock University

If you would like to receive a copy of a summary of the results of this study by email, please complete the following information:

Name: ____

Email: ____

If you would like to receive a copy of a summary of the results of this study by mail, please complete the following information:

Name: ____

Address: ____

City: ____

Postal Code: ____

APPENDIX C – RESEARCH ETHICS BOARD APPROVAL CERTIFICATE

Brock University
Office of Research Ethics
Tel: 905-688-5550 ext. 3035
Email: reb@brocku.ca

Health Science Research Ethics Board

Certificate of Ethics Clearance for Human Participant Research

DATE:	11/19/2020		
PRINCIPAL INVESTIGATOR:	BEAUDETTE, Shawn - Kinesiology		
FILE:	20-086 - BEAUDETTE		
TYPE:	Masters Thesis/Project	STUDENT: SUPERVISOR:	Paul & Aurora Goncharow & Battis Shawn Beaudette

TITLE: Assessing the Utility of a Video-Based Motion Capture Alternative in the Assessment of Lumbar Spine Movement Kinematics

ETHICS CLEARANCE GRANTED

Type of Clearance: NEW — Expiry Date: 11/1/2021

The Brock University Health Science Research Ethics Board has reviewed the above named research proposal and considers the procedures, as described by the applicant, to conform to the University's ethical standards and the Tri-Council Policy Statement. Clearance granted from **11/19/2020** to **11/1/2021**.

The Tri-Council Policy Statement requires that ongoing research be monitored by, at a minimum, an annual report. Should your project extend beyond the expiry date, you are required to submit a Renewal form before 11/1/2021. Continued clearance is contingent on timely submission of reports.

To comply with the Tri-Council Policy Statement, you must also submit a final report upon completion of your project. All report forms can be found on the Office of Research Ethics web page at https://brocku.ca/research-at-brock/office-of-research-services/research-ethics-office/#application-forms

In addition, throughout your research, you must report promptly to the REB:

a) Changes increasing the risk to the participant(s) and/or affecting significantly the conduct of the study;
b) All adverse and/or unanticipated experiences or events that may have real or potential unfavourable implications for participants;
c) New information that may adversely affect the safety of the participants or the conduct of the study;
d) Any changes in your source of funding or new funding to a previously unfunded project.

We wish you success with your research.

Approved:

Craig Tokuno, Chair
Health Science Research Ethics Board

Note: Brock University is accountable for the research carried out in its own jurisdiction or under its auspices and may refuse certain research even though the REB has found it ethically acceptable.

If research participants are in the care of a health facility, at a school, or other institution or community organization, it is the responsibility of the Principal Investigator to ensure that the ethical guidelines and clearance of those facilities or institutions are obtained and filed with the REB prior to the initiation of research at that site.