AN AUTONOMOUS METHOD FOR MEASURING 3D JOINT KINEMATICS FROM 2D XRAY IMAGES

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
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This is the dedication tex file, which should have been set in the main file using the command `\setDedicationFile{Drive:/file/location/dedicationFile}`. Keep in mind this should be written in first person; eg “I dedicate this to all those people that let me crawl into a cave and disappear while I learned way too much about way too specific of a subject in order to make a meaningful contribution to my field.”

ACKNOWLEDGEMENTS

This is the acknowledgments tex file, which should have been set in the main file using the command `\setAcknowledgementsFile{Drive:/file/location/acknowledgementsFile}`.

Keep in mind this should be written in first person, eg; "I thank my chair for his patience with my random tangents and endless questions and his subsequent (and often lengthy) explanations. I especially appreciate him refraining from voicing how dumb some of those questions were, despite me feeling like a moron nonetheless."

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LIST OF ABBREVIATIONS

TKA Total Knee Arthroplasty. This is the complete or partial resurfacing of the articulating surfaces in the knee.

TSA Total Shoulder Arthroplasty. This is the complete resurfacing of the articulating surfaces in the shoulder.

rTSA Reverse Total Shoulder Arthroplasty. This is a TSA procedure where the ”ball and socket” mechanism is reversed.

ML Machine Learning. This is the process of feeding a computer inputs and outputs in order to determine an algorithm that goes from input $\longrightarrow$ output

CNN Convolutional Neural Network. This is a type of neural network that uses convolution kernels as the operation between each of the layers

HRNet High Resolution Convolutional Neural Network. This is a specific CNN created by (ADD CITATION) (https://github.com/HRNet)

Abstract of Dissertation Presented to the Graduate School
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Chair: Scott Banks
Major: Mechanical Engineering

`Abstract Placeholder`

This is a brief outline of the main points to make for the abstract

The function of joints The main function of our joints is to support dynamic loaded motion

Joint Pathologies Many joint pathologies express themselves during motion. i.e. most of the pain that someone might express would occur during motions like walking or running

Clinical Tools available Clinicians can't measure the motion of joints during these painful exercises.

Joint Cost These diseases cost, on average $XYZ dollars per year in direct and related costs. Despite this, there are no tools for clinicians to measure the fundamental motions of those joints

Existing Methods Existing methods are far too time-intensive, expensive, invasive, or unreliable for clinical use.

Autonomous Methods We know that clinicians would eagerly adopt these technologies!

The primary function of synovial joints is to support the dynamic, loaded motion of the human body. This motion is supported by bony and connective tissue working together with a

series of muscles and ligaments to move various parts of the human body. Most joint ailments arise during motion, and most treatments attempt to restore normative motion to the affected joint(s). The financial burden of musculoskeletal issues in the united states is approaching $XYZ dollars (CITE). Despite that staggering number, clinicians do not have the tools that they need to measure the motion of these joints, espically in a clinical setting. Historical methods of quantifying joint pathology are entirely static.

In the past, researchers have been able to create methods of determining the motion of joints. Despite their efforts, these methods still rely heavily on invasive techinques, inaccurate measurements, or time consuming computtations. Each of these make them impossible to introduce into a cliniical setting.

Utilizing computatiuonal speed-ups associated with increased computer power, various machine learning techinques have come into play for different computer vision problems. This paper explores the different cases of making an autonomous system that can quantify the 6 DOF kinematics of various joints using only 2D fluoroscopic imaging systems.

CHAPTER 1
INTRODUCTION

The primary function of human synovial joints is to support the dynamic motion of the musculoskeletal system. The diseases that typically affect these systems manifest during movement, with mild to severe pain arising during specific activities or during particular ranges of motion. Unsurprisingly, the financial burden of musculoskeletal diseases is roughly USD 300 billion per year in direct and indirect costs [1]. One of the most common conditions affecting human joints is osteoarthritis, which involves the progressive loss of the cartilage between the joint surfaces over time [17]. A highly effective solution for osteoarthritis is arthroplasty, which involves a partial or complete removal and resurfacing of the affected joint with polymeric and metallic components intended to relieve pain and restore a degree of natural function and motion. Despite being highly effective, roughly 20% of patients receiving total knee arthroplasty express some form of dissatisfaction, usually manifested as pain, instability or stiffness during movement ([2], [16], [5]). Surprisingly, standard clinical musculoskeletal diagnostic methods are entirely static. That is, clinicians do not have at their disposal clinically practical ways to quantify skeletal motion during weight-bearing or dynamic movement when most pain symptoms occur. Unfortunately, most of the tools used to accurately quantify 3D dynamic motion (e.g., 3D motion capture, radiostereometry, fluoroscopic model/image registration) are prohibitively expensive or impractical to use in clinical settings. Methods using single-plane fluoroscopic or flat-panel imaging with 3D-to-2D model-image registration have been used since the 1990s. They have been shown to provide sufficient accuracy for many clinical joint assessment applications , including natural and replaced knees ([3], [4], [11], [22]), natural and replaced shoulders ([12], [14], [21], [13], [9]), and extremities ([20], [10], [7], [6], [18]). One benefit of this approach is that suitable images can be acquired with equipment commonly found in most hospitals. The main impediment for this technology to be used clinically is the time and expense of human operators to supervise the model-image registration process. If the need for human supervision for model-image registration were eliminated, then fluoroscopic imaging could provide a reliable, inexpensive, and accurate method to provide 3D dynamic joint kinematics in a clinical setting. State-of-the-art techniques for generating kinematics using model-image registration involve numerical optimization techniques that iteratively match bone or implant model projections in dynamic x-ray images ([15], [8], [19]). These methods provide accurate 3D bone or implant kinematics when given a rough initial pose estimate for numerical optimization ([8]). However, these methods still require human input for an initial pose estimate, making them impractical for clinical use. Recent advancements in computational capabilities and machine learning algorithms provide tools that are well-suited to replace human supervision for a range of time-consuming tasks including model-image registration. In particular, convolutional neural networks can be trained to provide the image segmentation and pose-estimation capabilities required to autonomously extract knee implant kinematics from single-plane video fluoroscopy. Neural networks can be trained to segment the pixels belonging to a particular knee implant (femoral or tibial), and this pixel information can be used in a numerical optimizer to generate an implant's 3D pose. Alternatively, a neural network can be used directly for pose-regression, using image data as input values and 3D object pose as output. This latter technique relies on the network's ability to extract latent characteristics that determine the pose, not an object-oriented cost function to minimize pose error. This regression approach will be sensitive to study conditions, including implant geometry, projection distance and image size, all of which are ”lost” when viewing a single-plane image as only a collection of pixels.

CHAPTER 2
RESEARCH PROPOSAL

This is the introduction to the literature review that I am going to write

$$\frac{hello}{goodbye} \tag{2-1}$$

CHAPTER 3
EXAMPLES OF EDITOR/AUTHOR TOOLS, TABLES, AND IMAGES

REFERENCES

[1] *BMUS: The Burden of Musculoskeletal Diseases in the United States*, https://www.boneandjointburden.org/.

[2] P. N. Baker, J. H. van der Meulen, J. Lewsey, and P. J. Gregg, *The role of pain and function in determining patient satisfaction after total knee replacement: DATA FROM THE NATIONAL JOINT REGISTRY FOR ENGLAND AND WALES*, The Journal of Bone and Joint Surgery. British volume **89-B** (2007), no. 7, 893–900.

[3] S.A. Banks and W.A. Hodge, *Accurate measurement of three-dimensional knee replacement kinematics using single-plane fluoroscopy*, IEEE Transactions on Biomedical Engineering **43** (1996), no. 6, 638–649.

[4] Scott A. Banks, George D. Markovich, and W.Andrew Hodge, *In vivo kinematics of cruciate-retaining and -substituting knee arthroplasties*, The Journal of Arthroplasty **12** (1997), no. 3, 297–304.

[5] Robert B. Bourne, Bert M. Chesworth, Aileen M. Davis, Nizar N. Mahomed, and Kory D. J. Charron, *Patient Satisfaction after Total Knee Arthroplasty: Who is Satisfied and Who is Not?*, Clinical Orthopaedics & Related Research **468** (2010), no. 1, 57–63.

[6] F. Cenni, A. Leardini, M. Pieri, L. Berti, C. Belvedere, M. Romagnoli, and S. Giannini, *Functional performance of a total ankle replacement: Thorough assessment by combining gait and fluoroscopic analyses*, Clinical Biomechanics **28** (2013), no. 1, 79–87.

[7] Francesco Cenni, Alberto Leardini, Claudio Belvedere, Francesca Buganè, Karin Cremonini, Maria T. Miscione, and Sandro Giannini, *Kinematics of the Three Components of a Total Ankle Replacement:* In Vivo *Fluoroscopic Analysis*, Foot & Ankle International **33** (2012), no. 4, 290–300.

[8] P. D. L. Flood and Scott A. Banks, *Automated registration of 3-D knee implant models to fluoroscopic images using lipschitzian optimization*, IEEE Transactions on Medical Imaging **37** (2018), no. 1, 326–335.

[9] Takehiro Kijima, Keisuke Matsuki, Nobuyasu Ochiai, Takeshi Yamaguchi, Yu Sasaki, Eiko Hashimoto, Yasuhito Sasaki, Hironori Yamazaki, Tomonori Kenmoku, Satoshi Yamaguchi, Yoshitada Masuda, Hideo Umekita, Scott A. Banks, and Kazuhisa Takahashi, *In vivo 3-dimensional analysis of scapular and glenohumeral kinematics: Comparison of symptomatic or asymptomatic shoulders with rotator cuff tears and healthy shoulders*, Journal of Shoulder and Elbow Surgery **24** (2015), no. 11, 1817–1826.

[10] Renate List, Mauro Foresti, Hans Gerber, Jörg Goldhahn, Pascal Rippstein, and Edgar Stüssi, *Three-Dimensional Kinematics of an Unconstrained Ankle Arthroplasty: A Preliminary* In Vivo *Videofluoroscopic Feasibility Study*, Foot & Ankle International **33** (2012), no. 10, 883–892.

[11] M.R. Mahfouz, W.A. Hoff, R.D. Komistek, and D.A. Dennis, *A robust method for registration of three-dimensional knee implant models to two-dimensional fluoroscopy images*, IEEE Transactions on Medical Imaging **22** (2003), no. 12, 1561–1574.

[12] Keisuke Matsuki, Kei O. Matsuki, Shang Mu, Tomonori Kenmoku, Satoshi Yamaguchi, Nobuyasu Ochiai, Takahisa Sasho, Hiroyuki Sugaya, Tomoaki Toyone, Yuichi Wada, Kazuhisa Takahashi, and Scott A. Banks, *In vivo 3D analysis of clavicular kinematics during scapular plane abduction: Comparison of dominant and non-dominant shoulders*, Gait & Posture **39** (2014), no. 1, 625–627.

[13] Keisuke Matsuki, Kei O. Matsuki, Shang Mu, Satoshi Yamaguchi, Nobuyasu Ochiai, Takahisa Sasho, Hiroyuki Sugaya, Tomoaki Toyone, Yuichi Wada, Kazuhisa Takahashi, and Scott A. Banks, *In vivo 3-dimensional analysis of scapular kinematics: Comparison of dominant and nondominant shoulders*, Journal of Shoulder and Elbow Surgery **20** (2011), no. 4, 659–665.

[14] Keisuke Matsuki, Kei O. Matsuki, Satoshi Yamaguchi, Nobuyasu Ochiai, Takahisa Sasho, Hiroyuki Sugaya, Tomoaki Toyone, Yuichi Wada, Kazuhisa Takahashi, and Scott A. Banks, *Dynamic In Vivo Glenohumeral Kinematics During Scapular Plane Abduction in Healthy Shoulders*, Journal of Orthopaedic & Sports Physical Therapy **42** (2012), no. 2, 96–104.

[15] Barbara Postolka, Renate List, Benedikt Thelen, Pascal Schütz, William R. Taylor, and Guoyan Zheng, *Evaluation of an intensity-based algorithm for 2D/3D registration of natural knee videofluoroscopy data*, Medical Engineering & Physics **77** (2020), 107–113.

[16] C. E. H. Scott, C. R. Howie, D. MacDonald, and L. C. Biant, *Predicting dissatisfaction following total knee replacement: A PROSPECTIVE STUDY OF 1217 PATIENTS*, The Journal of Bone and Joint Surgery. British volume **92-B** (2010), no. 9, 1253–1258.

[17] Leena Sharma and Francis Berenbaum (eds.), *Osteoarthritis: A companion to Rheumatology*, Mosby, Philadelphia, 2007.

[18] L. Tersi, S. Fantozzi, and R. Stagni, *3D Elbow Kinematics with Monoplanar Fluoroscopy: In Silico Evaluation*, EURASIP Journal on Advances in Signal Processing **2010** (2009), no. 1, 142989.

[19] Tsung-Yuan Tsai, Tung-Wu Lu, Chung-Ming Chen, Mei-Ying Kuo, and Horng-Chaung Hsu, *A volumetric model-based 2D to 3D registration method for measuring kinematics of natural knees with single-plane fluoroscopy: 2D/3D registration method for measuring natural knee kinematics*, Medical Physics **37** (2010), no. 3, 1273–1284.

[20] Satoshi Yamaguchi, Takahisa Sasho, Hideyuki Kato, Yuji Kuroyanagi, and Scott A. Banks, *Ankle and Subtalar Kinematics during Dorsiflexion-Plantarflexion Activities*, Foot & Ankle International **30** (2009), no. 4, 361–366.

[21] Zhonglin Zhu, Daniel F. Massimini, Guangzhi Wang, Jon J.P. Warner, and Guoan Li, *The accuracy and repeatability of an automatic 2D–3D fluoroscopic image-model registration technique for determining shoulder joint kinematics*, Medical Engineering & Physics **34** (2012), no. 9, 1303–1309.

[22] S. Zuffi, A. Leardini, F. Catani, S. Fantozzi, and A. Cappello, *A model-based method for the reconstruction of total knee replacement kinematics*, IEEE Transactions on Medical Imaging **18** (Oct./1999), no. 10, 981–991.

BIOGRAPHICAL SKETCH

Andrew Jensen is a Florida native from Sarasota, Florida. He attended the University of Florida for his undergraduate degree in Mechanical Engineer, for which he received high honors. He took a brief hiatus from school to work at an orthopaedic solutions company, Exactech. The COVID-19 pandemic cut his time at Exactech short, so he joined the Gary J Miller Orthopaedic Biomechanics Laboratory as a part-time researcher during the summer leading up to his first official semester of graduate school.

Andrew enjoys being outdoors, hiking, reading, and doing different things.