Automated Spinal Segmentation and Remote Monitor Calibration for Surgical Assessment

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Introduction

Background

The spine is a mobile structure that allows the body to bend, twist, and lift. However, spine surgeons currently do not have a method of quantitative motion analysis for diagnosis and surgery pre-planning. Current spinal imaging techniques involve X-Rays, CT scans, and MRIs, which provide static images that are not representative of the spinal curvature of the patient during routine daily activities. As a result of limited imaging options, spinal fusion surgeries are often improperly prescribed. Our mentor's team, Curve Assure, prototyped a device that can be placed on the back of patients to give doctors an insight into the behavior of the spine when the patient is moving over a longer period of time. However, to provide actionable insights for doctors, sensor readings must be augmented with spinal imaging techniques to produce a personalized quantitative motion model.

Goal

Our project aims to augment Curve Assure's spinal IMUs with computer vision techniques. Our project has multiple phases. The first phase entails the development of a method capable of estimating an approximate spinal curve of the patient using monocular video. A pre-trained pose-estimation model will be adapted and trained using a transfer learning approach to produce spinal key points. Spinal key points, paired with a volumetric pose estimation model, will be used to produce an approximate spinal curve using splines in the pose estimation model. The second phase corresponds to the development of a transfer function that maps IMU data to spinal keypoint angles. This transfer function will be used to correlate IMU sensor data with the estimated spinal curve, producing a quantitative model of the patient's movement in 3D space. Lastly, the last phase entails deploying our method on the cloud and developing a pipeline that enables users to upload video and sensor data to the cloud and receive a quantitative model of the patient's spine.

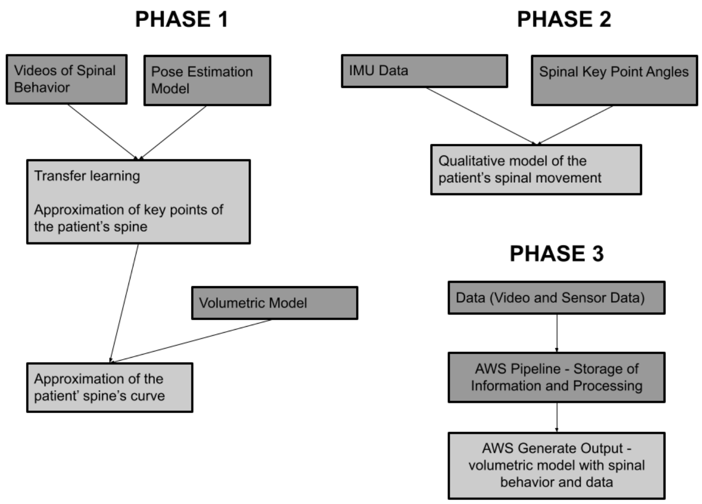

Figure 1 - Phases of This Project

Significance

Current methods of accessing eligibility for spinal fusion surgeries are complex and unclear. Up to 1.62 million instrumented spinal fusion procedures occur each year [1]. However, these surgeries suffer from complication and revision rates as high as 50% and 36% respectively [2]. One contribution to this shocking statistic is that these procedures are often improperly prescribed. 17% of spinal fusion surgeries are performed on patients who should not have been recommended for the procedure in the first place [3]. In fact, the variability regarding the eligibility assessment can drastically change for patients. One study showed that even expert assessments can drastically change for a given patient from one day to another. These patients often suffer from negative outcomes as well as costly medical bills that are unnecessary.

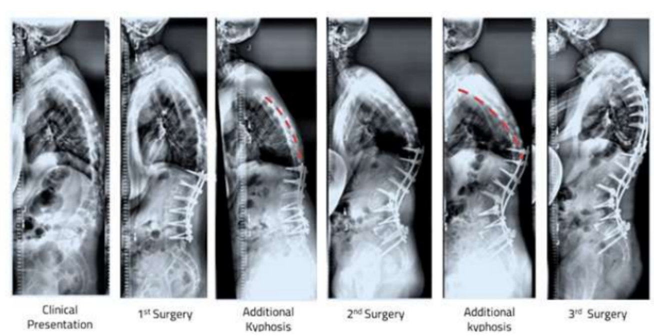

Figure 2 - Patient With multiple revisions [4]

In the example above, a patient had to undergo multiple surgeries, as the first two surgeries did not produce the desired outcome.

Therefore, this project aims to decrease the improper prescription of spinal surgery, by providing doctors with a dynamic view of the patient's spine. By placing the sensors of these patients and utilizing our model and transfer function, our team is able to produce a comprehensive image of the behavior of the spine, thus providing doctors with a better means of assessing if their patient is eligible for a procedure. Moreover, by deploying our solution to the cloud, our team ensures the solution is accessible to doctors around the world without the need for specialized computational equipment.

Technical Approach

Spinal Curve Estimation

The task of spinal curve estimation is divided into two sub-tasks, spinal keypoint estimation, and spinal curve interpolation. The integration of these two components can be found in Figure 3. We discuss each separately.

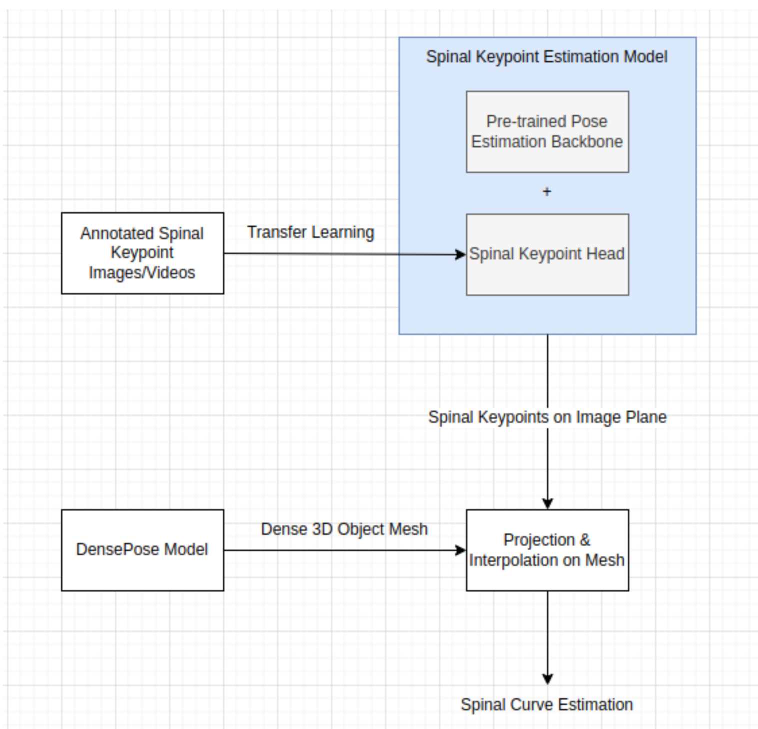

Figure 3 - Spinal Curve Estimation Pipeline

Spinal Keypoint Estimation

The task of spinal keypoint estimation involves the consistent detection, and tracking, of spinal key points on a patient from monocular video. Formally, given a video, represented as a tensor of shape

$V = (F, C, H, W)$, where F is the number of frames, C is the number of channels (3 for RGB, 1 for grayscale), and H, W are the height and width of the frames respectively. Then, we must produce a function f such that $f(V) = K$, where K is a tensor of shape $(4, F, 2)$, corresponding to 4 key points found for each frame for both axes (u, v) in image coordinates.

To produce f, we leverage deep learning and the paradigm of transfer learning. Specifically, we will take a pre-trained pose-estimation model (OpenPose [10], PoseNet [11], DensePose [12], etc.) and extract its feature-detection backbone. As virtually all pose-estimation models are CNN-based, the backbones learned by these models will provide a latent image or video representation that encapsulates information useful to the task of pose estimation. Then, we will concatenate our own spinal-keypoint head, which will be used for the downstream task of spinal keypoint prediction. The spinal keypoint head will consist of a shallow series of fully connected layers. The specific depth and width of these layers, as well as the loss and activation functions involved, are yet to be specified and will be determined empirically with their impact on downstream accuracy.

We will explore various transfer learning approaches to train our spinal keypoint head. First, we will simply freeze the pose-estimation backbone and train the spinal keypoint head in a standard supervised setting. Then, we will explore various state-of-the-art few-shot transfer learning techniques, such as SpotTune [8] and surgical finetuning [9], and compare the results empirically.

Spinal Curve Interpolation

The task of spinal curve interpolation involves the interpolation of spinal key points on a volumetric mesh to produce a function approximating the spinal curve. Formally, given a tensor of key points K as described above, and a set of points P representing a volumetric mesh of the patient, we must estimate the function $g(K, P)$ that best interpolates the points K, constrained by the mesh P.

To produce g, we will explore a variety of approaches. First, we will begin with simple bilinear interpolation between the spinal key points and the points produced by the volumetric mesh. This approach will serve as a baseline for comparison of future results. Next, we will explore more sophisticated approaches to interpolation, such as spline interpolation, inverse distance weighting, and radial-basis function interpolation [5][6][7].

Sensor Transfer Function

We will develop a transfer function that utilizes patient IMU data in conjunction with estimated spinal key points to produce clinically relevant spinal range of motion (ROM) data. The transfer function takes inputs from the computer vision system's predicted 3D spine key points, represented by the tensor in the shape $(4, F, 2)$ as previously mentioned, and the IMUs orientation data, represented by the quaternion $q_t = (q_1, q_2, q_3, q_4)$, to compute estimated joint angles for each of the four major spinal regions in the sagittal and coronal planes. We will implement the function in two phases, first using a simple transfer function and later applying a robust transfer function.

Simple Transfer Function (Callibration only)

Using the 2D spinal reference frames found from the spinal key points, we will apply a simple linear function to combine the orientation data from the IMU and the positions of the key points to calculate angles between each of the spine segments. Patient movement is isolated to one plane in the procedure. We can calculate the plane of movement given IMU orientations in that plane with the following calculations:

1. For the cervical IMU placed on the neck, omit the pitch and yaw axis and only consider the roll axis
2. For the other IMUs placed on the spine, only consider the pitch and yaw axis.
3. With an output of the spinal estimation model with the patient in the standing position, compute the line orthogonal to the tangent to each key point on the spinal curve $g(x)$. Use the orthogonal line to set the pitch and yaw axes to 0 and 90 degrees respectively. For the cervical IMU, set the axis to 0.
4. Compute relative angles between the IMUs

Robust Transfer Function

The simple transfer function will be inaccurate due to variations in the placement of the IMU. To implement a robust transfer function, we plan on finding the orientations of the IMU and mapping a plane to the local orientations, applying an averaging function that omits outliers and noise. The resulting plane will be transformed into the X-Y coordinate plane of the IMU sensors. Using the orthogonal line obtained from the spinal curve, we will align the X-Y plane of the IMU sensor with a plane projected in 3D space formed by the lines orthogonal and tangent to our key points on the spinal curve. The resulting transformation between the IMU sensor and spinal key points will be used to estimate the relative orientations of each IMU. These orientations will be used to find the angles between each spinal segment.

Management Plan

Deliverables

Minimum (Expected delivery: April 7)

- Simple transfer function for translating IMU data and spinal keypoints to estimated spinal joint angles.
- Spinal estimation model capable of detecting key points on the spine from monocular video.

- Detailed documentation of interface and code structure between the two major components (transfer function & spinal estimation).

Expected (Expected delivery: April 28)

- Spinal estimation model can estimate spinal curvature and segment spinal sections through volumetric estimation and interpolation from monocular video.
- Amazon Web Services (AWS) workflow and infrastructure for model training and testing for future development.
- Detailed procedure for clinical use of the product including patient orientation, patient movement, and sensor location designed to produce the most descriptive spinal model of the patient.

Maximum (Expected delivery: TBD)

- AWS pipeline that allows for the remote upload of patient videos and IMU data and performs analysis in the cloud, returning the spinal model's output.
- Detailed procedure and method for sensor calibration, so as to reduce the impact of sensor drift and position prediction errors over the 48-hour data collection period.
- Software that creates a 3D volumetric model of the patient, enabling the demonstration of their posture/activity to surgeons utilizing either Blender or Maya.

Dependencies

If dependency deadlines are not met, one of two actions will be taken: alternative solutions will be implemented or checkpoints will be pushed back.

Software

- Computing power will be acquired from the following:
    - Personal laptops used by each team member provide sufficient computing power and support for processing the video while also processing information from the sensor data. *Deadline not applicable.*
    - Amazon Web Services (AWS) EC2 instances, virtual machines with configurable hardware, will be utilized in case our personal computer's processing power is insufficient. However, in order to run on AWS platforms, our team requires AWS credits. *Deadline to obtain: March 6th, Contingency: In general, if the credits cannot be obtained, our team plans to depend on AWS minimally or completely resort to our own computers.*
- Cloud-based services are required to assist in processing and capturing data. The following AWS services may be utilized:

    - S3 - storage, Sagemaker - Machine learning development space, Lambda/SQS - triggers to activate other AWS services, Amazon Kinesis Video Streams - processing video for machine learning

  Our team needs to ensure that each member has the appropriate IAM roles in order to access these services, alongside having the necessary AWS credits to utilize the above services. *Deadline to Obtain: March 6th, Contingency: In the event, our team cannot obtain AWS credits, our team will use a personal AWS using our own finances, but only in a limited capacity.*

- Access to pre-trained pose models - Our team needs to have access to pre-trained pose estimation models used for transfer learning and volumetric estimation. Most of these models are open source, and will simply need to be installed and compiled. *Deadline to Obtain: Mar 6th*

Footage for testing and validation:

- Access to videos (train & test data) - In order to train our model and validate our results, there must be access to videos that feature patients in a series of environments. The videos will need to be visually diverse to ensure model generalization. *Deadline to Obtain: March 6th. Contingency: Our team will film our own videos.*
- IMU Data - Data from the IMUs needs to be acquired, specifically those that come from the sample individuals moving according to the defined procedure for movement. *Deadline to Obtain: March 6th*

Testing

- IMU Sensors - IMUs will be acquired from Evan once the team has felt that it is appropriate to proceed to the test phase. The current scheduling for testing is around the second to last week of April. *Deadline to Acquire: April 17th*

Mentors

- **Youseph Yazdi**
  Director, Center for Bioengineering Innovation and Design
  Expertise in medical device development

- **Nicholas Theodore**
  Director, Johns Hopkins Neurosurgical Spine Department
  Expertise in spinal anatomy and surgery

- **Evan Haase**
  MSE Candidate, Center for Bioengineering Innovation and Design

Expertise in sensor technology and computer vision

- **Antony Fuleihan**
  MSE Candidate, Center for Bioengineering Innovation and Design
  Expertise in machine learning

- **Johns Williams**
  Complex Spine Fellow, Johns Hopkins Medicine
  Expertise in complex spinal reconstruction

- **Siri Khalsa**
  Instructor of Neurosurgery, Johns Hopkins Medicine
  Expertise in Neurosurgery

Team

- **Damiano Marsili**
  Undergraduate, Junior - Computer Science and Mathematics

- **Arijit Nukala**
  Undergraduate, Junior - Biomedical Engineering and Computer Science

- **Jonathan Young**
  Undergraduate, Junior - Computer Engineering
  MSE - Computer Science

The logistics of collaboration and team meetings go as follows:

- Meetings/Work Time 1-2 times a week in person on campus at Brody Learning Commons
- Weekly meetings with Evan Haas and Antony Fuleihan at 4:00 PM on Fridays via zoom. Additional meetings with Evan and Antony will be scheduled as needed.
- Meetings with Dr. Nicholas Theodore MD, Dr. Youseph Yazdi, Dr. Johns Williams, and Dr. Siri Khalsa as needed

Timeline

	February				**March**				**April**				**May**			
Preliminary Research																
Discussion with Mentors Regarding Approach																

Complete Project Proposal																
Software																
Pipeline for AWS Model Development																
Baseline transfer function																
Spinal Estimation Model capable of detect key points of spine																
Spinal Estimation model that can estimate spinal curvature through volumetric estimations and from monocular video																
Method for sensor calibration of sensor drift																
AWS pipeline that allows for the remote upload of patient videos and IMU data, and produces output																
Software that creates a 3D volumetric model of the patient, enabling the demonstration of their posture/activity																
Logistics																
Documentation of Interfaces																
Procedure to Acquire Patient Footage																
Documentation of Code																
Analysis of Code Functionality																
Record Footage and Data For Training																
Record Footage For Testing																
Final Evaluation																
Final Report and Presentation																

Responsibilities

- **Damiano Marsili**
  - Lead development on the spinal curve estimation model

- **Arijit Nukala**
  - Lead development on the transfer function model

- **Jonathan Young**
  - Set up AWS infrastructure and pipeline for testing, including setting up and managing virtual instances, file storage/sharing systems, etc.

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