



## **Literature Review:**

Automated Spinal Segmentation and Remote Monitor  
Calibration for Surgical Assessment

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Project # 8

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## Project Summary

Problem: IMU's on patient's spine lose accuracy over time, and hence need to be calibrated.

Project Goal: Create a pipeline to calibrate IMU's utilizing computer vision at the patient's home.

Individual Goals:

1. Estimate spinal key points and spinal curves on the patient's spine through computer vision
2. Deployment of a transfer function that maps the IMU data to spinal key points in 3D
3. Cloud deployment that enables user to upload sensor data to the cloud and receive a quantitative model of the patient's spinal movements.



## **Paper Selection:** Guo et al. “SpotTune: Transfer Learning through Adaptive Fine-tuning”

### Objective

- Develop a method for improved few-shot transfer learning on CNNs through adaptive fine-tuning of models

### Relevance to Project

- Spinal keypoint estimation model will be trained through transfer learning
  - Very limited keypoint-annotated videos
- Improved keypoint accuracy = improved IMU calibration

# Technical Approach

1. CNN is divided into 'residual blocks'
2. A policy network is trained by optimizing the Gumbel Softmax Distribution
  - a. Policy network outputs a routing decision for each block: "freeze" or "fine-tune"
3. Policy network is trained to minimize target loss
4. Policy network provides smart, instance-based fine-tuning of parameters

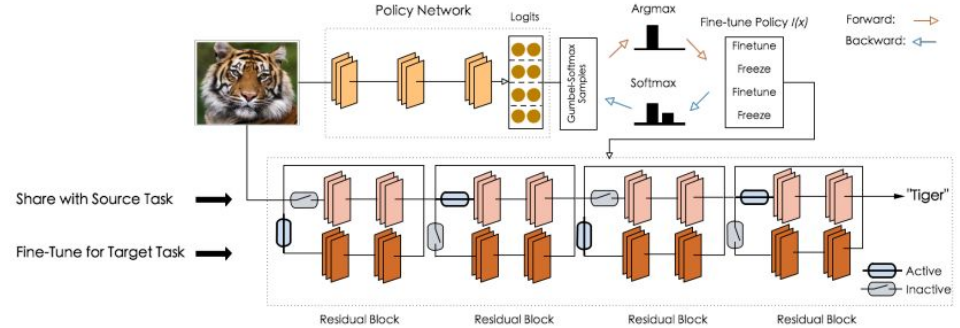


Figure 1 - SpotTune Method

Guo, Yunhui, et al. "Spottune: transfer learning through adaptive fine-tuning." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019.

$$y_i = \frac{e^{\frac{(\log(\pi_i) + g_i)}{\tau}}}{\sum_{j=1}^k e^{\frac{(\log(\pi_j) + g_j)}{\tau}}} \text{ for } i = 1, \dots, k$$

Figure 2 - Gumbel Softmax Distribution

<https://sassafra13.github.io/GumbelSoftmax/>



# Results

- Performs better than SOTA for transfer learning on 4 of 5 standard datasets for object detection
  - Testing: ResNet-101 is fine-tuned.
- Qualitatively:
  - Low-level differences show policies favoring earlier blocks
  - High-level differences show policies favoring later blocks

Model	CUBS	Stanford Cars	Flowers	WikiArt	Sketches
Feature Extractor	74.07%	70.81%	85.67%	61.60%	75.50%
Standard Fine-tuning	81.86%	89.74%	93.67%	75.60%	79.58%
Stochastic Fine-tuning	81.03%	88.94%	92.95%	73.06%	78.30%
Fine-tuning last-3	81.54%	88.21%	89.03%	72.68%	77.72%
Fine-tuning last-2	80.34%	85.36%	91.81%	70.82%	78.37%
Fine-tuning last-1	78.68%	81.73%	89.99%	68.96%	77.20%
Fine-tuning ResNet-101	82.13%	90.32%	94.21%	<b>76.52%</b>	78.92%
$L^2$ -SP	83.69%	91.08%	95.21%	75.38%	79.60%
SpotTune (running fine-tuned blocks)	82.36%	92.04%	93.49%	67.27%	78.88%
SpotTune (global-k)	83.48%	90.51%	<b>96.60%</b>	75.63%	80.02%
SpotTune	<b>84.03%</b>	<b>92.40%</b>	96.34%	75.77%	<b>80.20%</b>

Table 2. Results of *SpotTune* and baselines on CUBS, Stanford Cars, Flowers, WikiArt and Sketches.

Guo, Yunhui, et al. "Spottune: transfer learning through adaptive fine-tuning." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019.



# Critical Review

## Pros:


- Outperforms SOTA - notably outperforms manual fine-tuning
  - Allows us to provide transfer function presented in Paper 2 higher-accuracy keypoints

## Cons:

- Approach evaluated solely on object detection
- Method is image specific - will need a video implementation

## Key takeaway:

- Method will likely be used to train spinal keypoint estimation module.
  - Faster development time, higher accuracy



**Paper Selection:** Franco, Luca et al. “A novel IMU-based clinical assessment protocol for Axial Spondyloarthritis: a protocol validation study.”

Objective

- Determine the accuracy of measuring spinal angles using IMU based methods compared to gold-standard optical tracker measurement

Relevance to Project

- Our project requires the use of IMUs to determine the spinal range of motion (ROM) from spinal angles during movement
  - This paper provides the mathematical background for our project
- The kinematic constraints provided in the paper offer a starting point for our transfer function to convert IMU data to spinal angles

## Technical Approach

1. Place IMUs + Optical trackers on patient at key locations
2. Calibrate IMUs using kinematic constraints
3. Collect data from patient movements such as bending, flexion, etc
4. Calculate angles from quaternion outputs in MATLAB
5. Use minimum and maximum angles during movements to calculate ROM

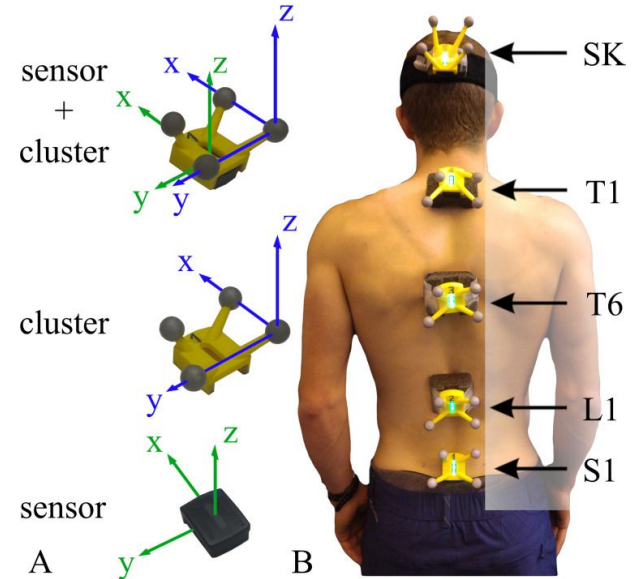


Figure 4 - Architecture of system

# Results

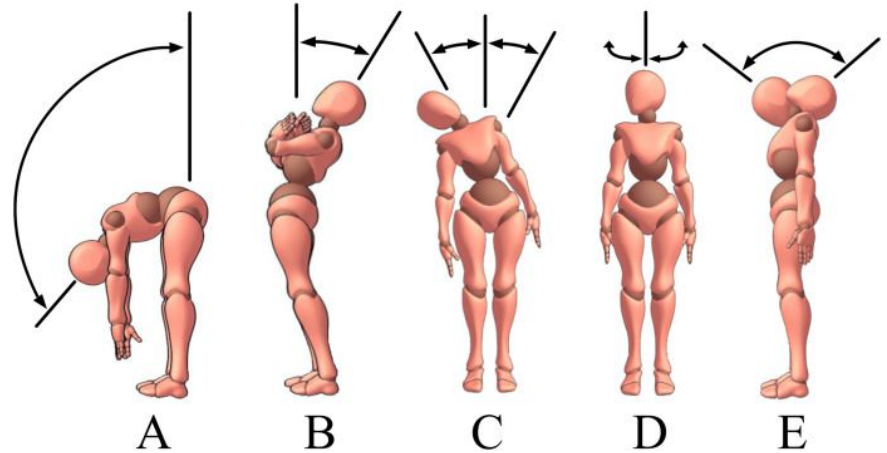
**Goal:** Prove that IMU based spinal ROM calculation can be accurate

**Method:** Create a procedure to collect ROM data and place IMUs for data collection


**Analysis:** Statistically compare IMU output ROMs to optical tracker ROMs

**Results Summary:** IMUs were found to contain some small error but were overall very close to optical tracker measurements

**Key takeaway:** IMU based measurement of spinal angles is accurate and can be done using simple equations provided in this paper



**Figure 5 - Movement Protocol for ROM Measurement**



**Paper Selection:** Ojog, I., Arias-Estrada, M., Gonzalez, J. A., & Flores, B. (2013). A cloud scalable platform for DICOM image analysis as a tool for remote medical support. In The Fifth International Conference on eHealth, Telemedicine, and Social Medicine. France.

### Objective

- Analyzing the feasibility of a pipeline to upload medical data (DICOM), process data through AWS (Amazon Web Services), and produce a semi-cloud based visualization of the analysis.

### Relevance to Project

- Our project requires a pipeline to upload and process data from the IMU's and camera via the cloud.
- Can help guide our project in terms of how to develop our own pipeline as well as the visualization interface that the doctor utilizes.

# Technical Approach

1. Authentication of the user
2. Upload to cloud storage or use existing medical data already in storage
3. Process the data via EC2 (virtual instance)
4. Produce output
5. View output in browser

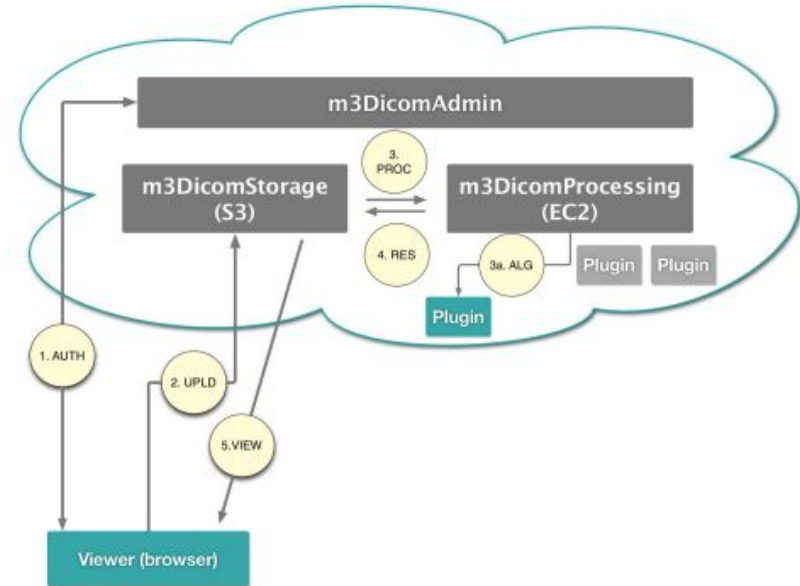


Figure 1 - Architecture of system

# Results

**Summary:** Robust, quick cloud processing processing. HTML visualization of results generated from cloud complex visualizations viable.

## Pros:

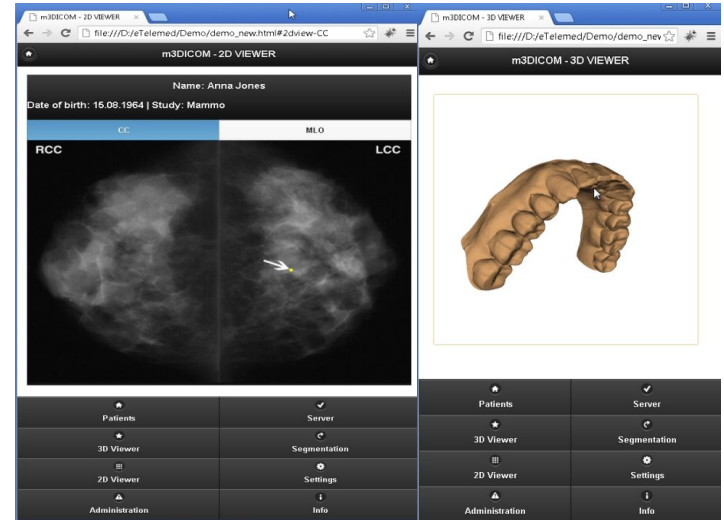
- Good job describing system architecture
- Demonstrated the wide range of applications that can be done

## Cons:

- Lacks detail regarding the low level cloud systems that regulate interaction between services

## Key takeaway:

- Cloud based uploading, processing, and visualizing data quickly and reliably is feasible - team will iterate on model



**Figure 2 - Breast Cancer Visualization**

**Figure 3 - Jaw Visualization**

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