

# Surgical Trainer and Navigator Final Report

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## **Introduction**

Assessing a surgeon's technical skill is a challenging task. Generally, novice surgeons take longer and perform steps more inefficiently than experts. There are currently no objective measures for surgeons' technical performance. Trainees are expected to have gained sufficient technical skill either by completing five years of training or by logging a minimum number of key procedures. Studies involving the tracking of hand movements during surgery have demonstrated a clear difference between novice and expert surgeons<sup>1</sup>. However, the sensors used are expensive and not widely available, and the previously reported results of number of movements and total distance travelled can be difficult to interpret.

Our mobile application, Surgical Trainer and Navigator (STAN), takes advantage of the recent widespread availability of wearable technology that can track motion in order to provide a more accessible way for surgeons to objectively assess their technical performance. STAN seeks to provide more meaningful feedback to surgeons in order to improve technical performance.

## **Overall Design and Block Diagram**

STAN uses Texas Instruments (TI) Bluetooth SensorTag sensors attached to the surgeon's wrists (with wristbands) in order to record accelerometer data. This data is processed and analyzed to give the user feedback on technical performance. STAN also allows for comparison of multiple recordings so that the user can view his/her progress.

The block diagram (Fig. 1) demonstrates the flow of data through our program.

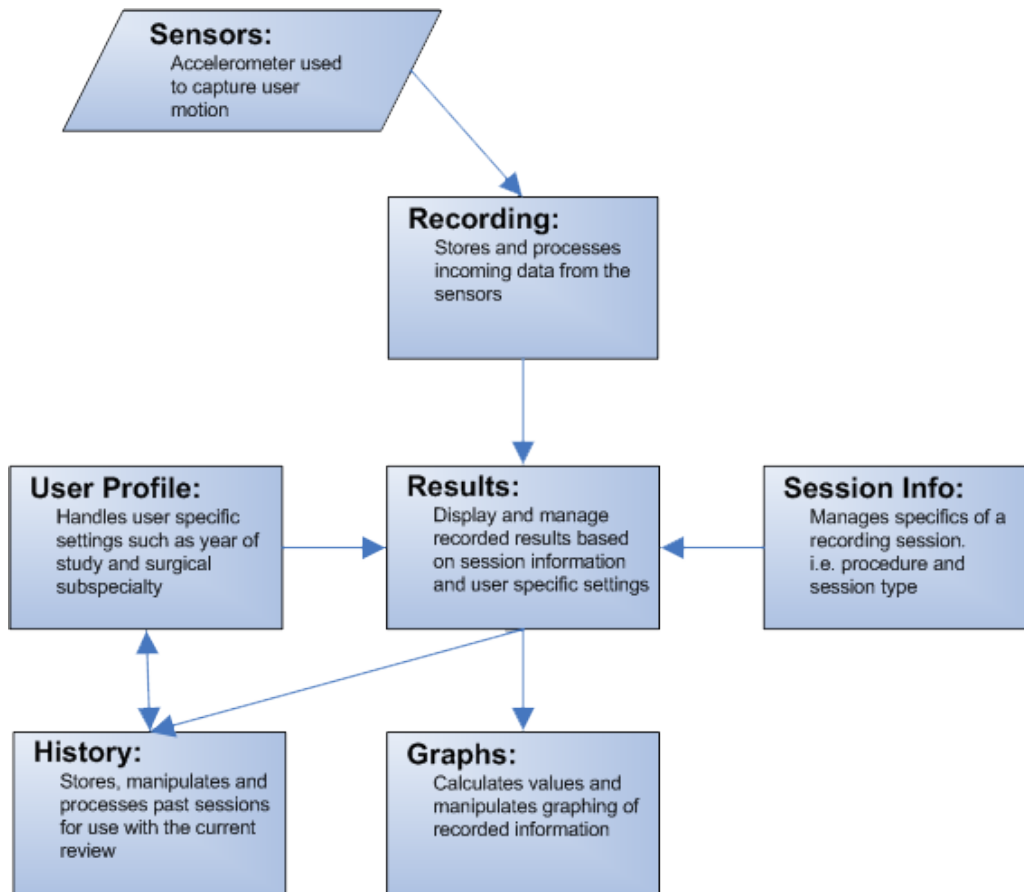


Figure 1. Data Flow Block Diagram

**Sensors:** This component represents the physical Bluetooth sensors that are attached to the user’s wrists, which feed accelerometer data to the program for recording.

**Recording:** This component represents the storage and processing of the data collected by the sensors.

**User Profile:** The User Profile represents the data specific to the application’s current user. This component was created with the idea of providing results and comparisons to other users with a similar level of experience.

**Session Info:** Session information was collected for the purposes of analysis. Originally we had hoped to have multiple different types of procedures. Due to time and difficulties, we only managed to accomplish the “Peg Transfer” task.

**Results:** The result component takes the data collected from the recording unit, processes it, and displays meaningful results as feedback to the user (See “Measurements” section).

**History:** History provides the ability to a) look at previous results by selecting the desired session, and b) see one’s improvement through progress graphs of Speed, Precision and Efficiency.

**Graphs:** This component graphs the desired values to give visual feedback to the user.

## Measurements

To derive measures of precision and efficiency, the following calculations were made: Firstly, the magnitude of the resultant acceleration was calculated with the formula:

$$a_{res} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

The accelerometer data used included gravitational acceleration, thus we needed a method to negate gravity’s effect in our calculations. Ideally, we would use the gyroscope to figure out the direction of gravity relative to the sensor and subtract the appropriate values from each component before calculating  $a_{res}$ . Since we were unable to acquire gyroscope data, we employed a different method.

Since the magnitude of gravity’s effect on the accelerometer is constant, every instance of the  $a_{res}$  measurement includes gravity in some combination of  $a_x$ ,  $a_y$  and  $a_z$ . Therefore, we cancelled out gravity’s effect by calculating the change of the magnitude of the resultant acceleration from one instance to the next.

$$\Delta a_{res_i} = a_{res_i} - a_{res_{i-1}} \quad (\text{green line Fig. 2})$$

This method is feasible because  $a_{res}$  is a magnitude and does not include direction. The  $\Delta a_{res}$  measurement was used with the following calculations.

### Precision

Precision was defined as controlled movements with small changes in resultant acceleration. Taking each change of resultant acceleration as a discrete movement, the sum of the distances that would result from each of those accelerations was calculated using the following formula:

$$\text{Precision} = \sum_{i=1}^n v_{i-1} t_i + \frac{1}{2} a_i t_i^2$$

Treating each acceleration as a discrete movement, we assumed that  $v_{i-1}$  will always equal 0 m/s. As a result, the formula simplifies to:

$$\text{Precision} = \sum_{i=1}^n \frac{1}{2} a_i t_i^2$$

Though this calculation does not represent the actual distance that the user moved (as we would need to know the user’s direction of movement to calculate that), it creates a consistent measure from one session to the next. The changes in acceleration from a user’s movement correlates to precision, and therefore, a smaller magnitude in precision would indicate better control of the user’s movement.

### Efficiency

Efficiency was defined as the number of movements a user made, consistent with efficiency measures reported in the literature<sup>1,2</sup>. Movement was defined as a cluster of large accelerations.

To count the number of movements, the net resultant acceleration graph was used (green line Fig. 2). Large clusters of acceleration were identified by examining the results of applying a local Gaussian smoothing to this graph (red line Fig. 2). By identifying an increase then drop in acceleration based on a threshold, the end of a movement was identified (blue spikes Fig. 2). Counting the number of identified “end of movements” led to the total number of reported movements, which represents efficiency.

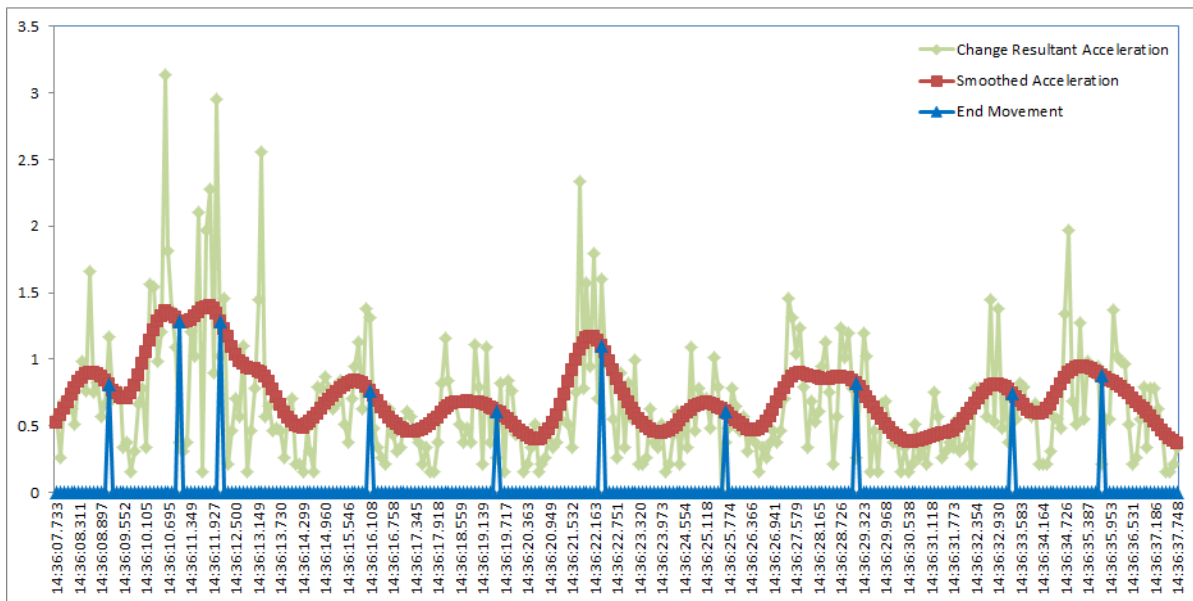
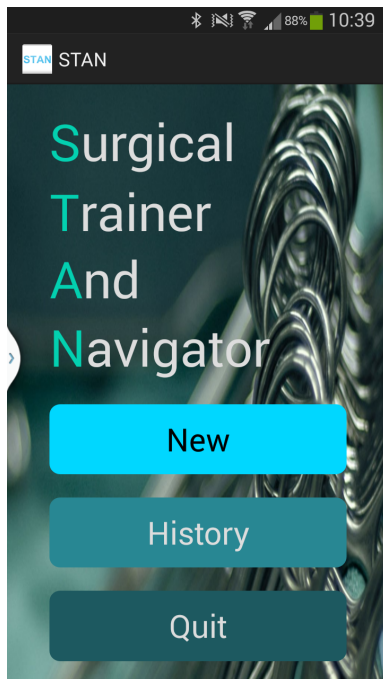
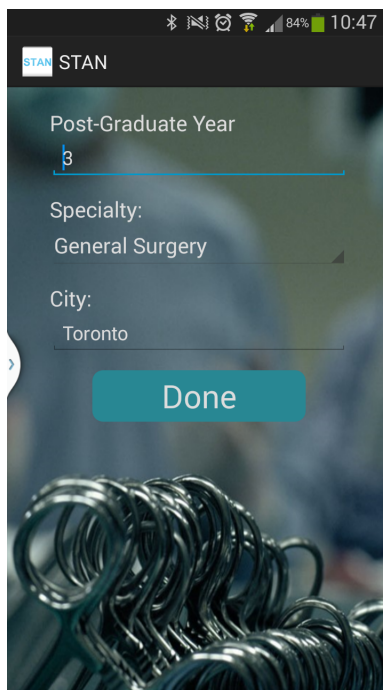


Figure 2. Data used for efficiency and precision calculation (green line); Analysis used for efficiency (red and blue lines)

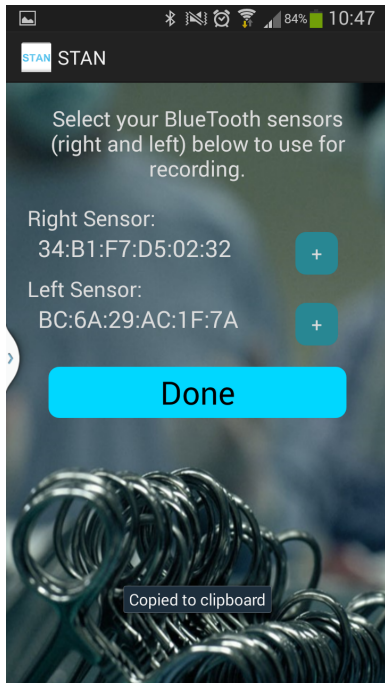
## Statement of Functionality and Screen Shots



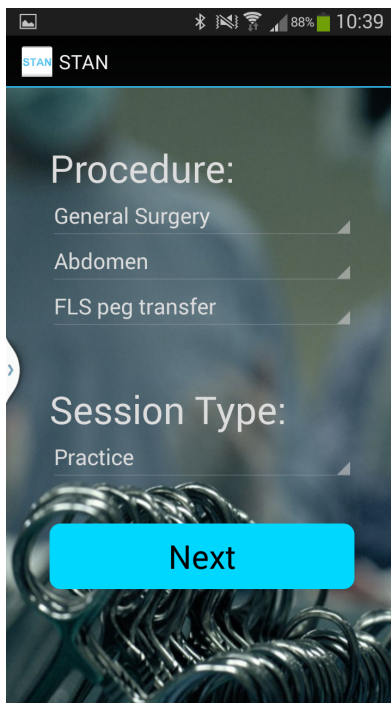
From the main menu, the user can start a new recording session or select historic information. From the options menu, the user can change “User Settings” and “Sensor Settings”.



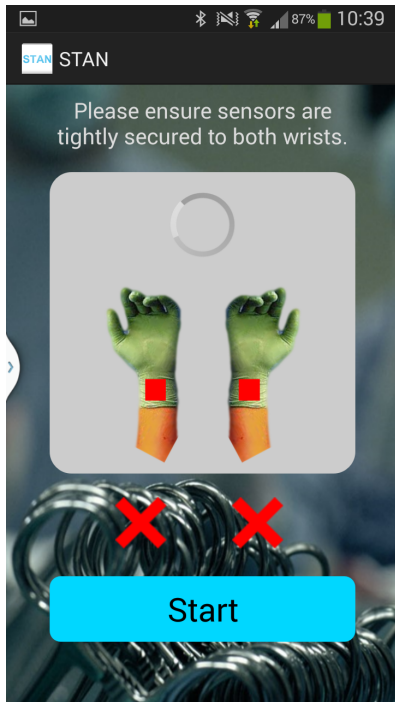
Through “User Settings” the user can enter his years of experience (by specifying post-graduate year, a common way to refer to experience level in surgery), select a specialty, and enter a city. This information was meant to facilitate comparison of results to those with similar experience, within same or different specialties, and from various cities. Unfortunately, we did not have sufficient time to incorporate this functionality into our application.



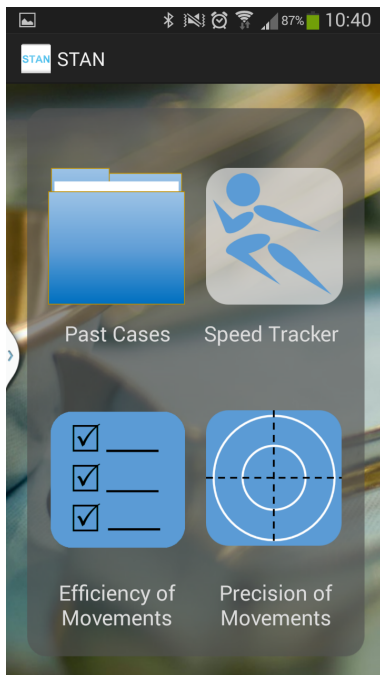
From “Sensor Settings” the user can select specific sensors that the application will use to avoid connecting to other Bluetooth devices in the area.



A “New” recording session allows the user to select the type of procedure to be recorded. A major category, a sub-category and a procedure type help to quickly refine one’s selection. Also, this page allows the user to select a session type (practice, simulated, or live).

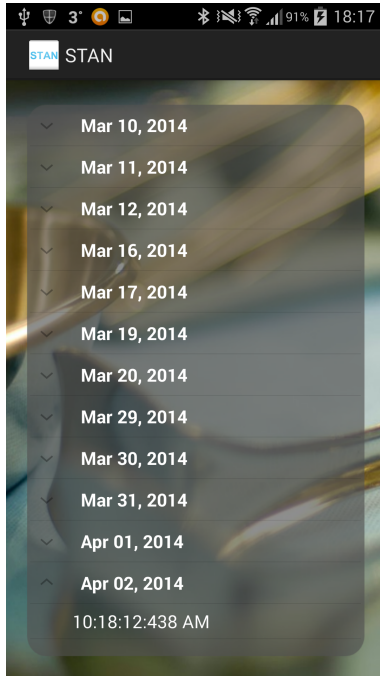


On this screen, the user is instructed to turn on the sensors. When the sensors are detected, the red Xs become green checks. By pressing “Start” (or using a gesture - pointing the left-wrist down and the right-wrist up), the recording session will commence.

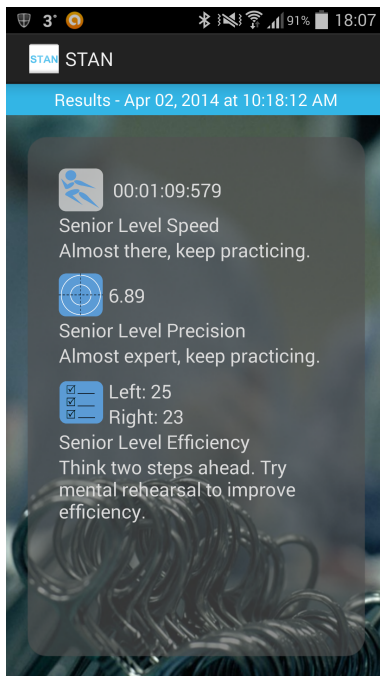


The user has four options when viewing history. The first option is to view individual results for previously recorded cases. The other three options display graphs of speed, efficiency, and precision to visualize progress.

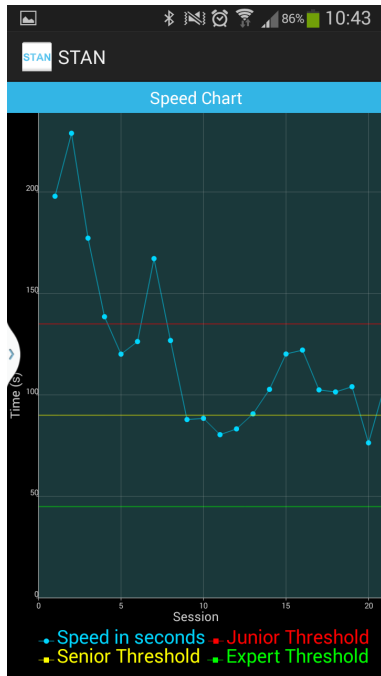




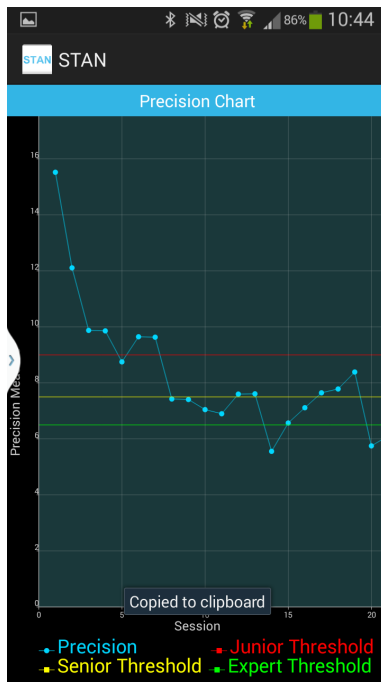
By selecting “Past Cases”, the user is presented a list, where he can choose to review individual results for a specific session.



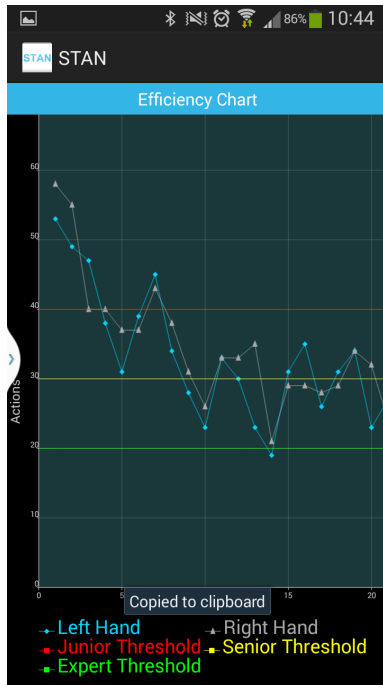
In this example, the result screen displays feedback to the user regarding his speed, precision, and efficiency. This page is seen immediately after stopping a recording or when reviewing previously recorded sessions. Each measurement provides a corresponding performance category (expert, senior, junior, or beginner) and tips to help the user improve future performances.



The History Speed Chart displays the time it took to complete a specific procedure by recorded session number. Three thresholds for expert, senior and junior performance are shown by green, yellow, and red horizontal lines, respectively, in each of the history charts. Here, the user can monitor his speed improvement.



The History Precision Chart displays the user’s “Precision of Movements” for a specific procedure by recorded session number. Here, the user can monitor improvement in precision.



The History Efficiency Chart displays the user's "Efficiency of Movements" for both the left and right hand, for a specific procedure by recorded session number. Here, the user can monitor improvement in efficiency for left and right hands.

## What did you learn? What would you do differently?

The main difficulties we had in creating this application were sensor limitations and data analysis. Specifically, we had connection issues with the BLE SensorTags as they would periodically enter sleep mode. Furthermore, the accelerometer data was available at ten times per second while the gyroscope data was available once per second. The inability to acquire gyroscope data at high frequency made us unable to calculate distance traveled, which previous studies reported as a component of efficiency. With respect to data analysis, we discovered that the raw data was difficult to interpret and required processing. Our investigation into data processing revealed that there are many complicated ways to do this. In the end, we chose simple processing methods such as Gaussian smoothing, having insufficient time to learn and implement more complicated analyses.

If we could do this again, we would obtain more consistent sensors that provide more frequent and accurate data. These sensors would also be able to collect accelerometer and gyroscope data simultaneously and at the same frequency. In addition, we would recruit a programmer with more data processing experience, including machine learning experience, who could help us to carry out more complex analyses of the data.

## Future Work

If we were to continue working on this application, we would aim to improve the accuracy of calculations, record more data, create specific feedback for more procedures, use gesture recognition, and add a social aspect to the application. We would acquire better sensors, which would enable us to estimate total distance traveled. We would record more data for different procedures and surgeon experience levels. Based on those additional recordings, we would create specific feedback for additional procedures. We would like to include gesture recognition using machine learning techniques so that the application could recognize vital components of procedures and how well they were performed. Lastly, we would incorporate a social aspect to the application, so that the user could export, share, and compare his data to users from other geographic locations.

## Contribution by Group Members

### *Rorik Henrikson*

As a programmer, Rorik provided the initial prototype code and rough user interface based on Dorotea's mock-ups, advised on the breakdown and pacing of tasks, and created the block diagram based on group discussions. He setup the code repository, oversaw the integration of the components, reviewed graphing libraries, selected and provided code for the graphing functionality, and created the class for loading and storing data. He worked with Kyle to integrate Bluetooth, and clean up functional details, and Dorotea to figure out meaningful performance categories. From these categories, he devised strategies for data analysis and provided the code that measures the results.

### *Dorotea Mutabdzic*

Dorotea provided ideas for possible applications in surgery. The decision to pursue STAN was made with Kyle and Rorik. Dorotea created mock-up screens and reviewed the literature on economy of hand movements during surgery to generate ideas for how best to analyze the data. Dorotea provided access to the Surgical Skills Centre, where recording sessions took place. Dorotea worked on user interface design with Kyle, making decisions about colour schemes, finding images, and designing icons. She worked on data analysis with Rorik making decisions about movement thresholds and developing performance categories. She developed tips for users for each performance category achieved. Lastly, Dorotea obtained a laparoscopic simulator for the final presentation demonstration and helped write the final report.

*Kyle Tsang*

Kyle's primary role was to learn about the different software components of the Texas Instruments (TI) Bluetooth SensorTags and how they could be connected to an Android device. A strong understanding of Bluetooth GATT profiles, Bluetooth Low Energy specifications, and Bluetooth service classes were required. After thorough research of the SensorTag wiki, Kyle created a stand-alone program to connect and display the accelerometer and gyroscope data from the two sensors. Afterwards, he integrated this program with the early user interface prototype. Throughout development, the code responsible for consistent connection of the Bluetooth sensors was modified. Kyle's secondary role was to improve the user interface design and layout scheme with Dorotea during the project's later phases. He also helped with the loading and storing of accelerometer data onto the phone.

**\*We agree to have our video, report, and code posted publicly.**

### **Apper Context**

As previously mentioned, there are currently no objective measures of surgeons' technical performance. There is good evidence that tracking hand movements allows for quantification of the learning curve for surgical procedures and for differentiation between expert and novice surgeons. The sensors used in previous studies have been expensive and not widely accessible. The development of a widely accessible mobile app that uses affordable and accessible sensors, would make objective assessment of technical performance feasible for all surgical trainees. This could greatly impact the evaluation and training methods used in surgical training.

The current evaluation methods are subjective rating scales filled out by clinical supervisors. Licensure to practice surgery independently is awarded upon graduation from a five year training program and adequate performance on final written and oral exams, in Canada. In the U.S., there is an additional requirement of logging a specified minimum number of key procedures. However, there is no measure of how well the logged procedures were done. There is no technical examination. Part of the reason for this is that it would be unfeasible for examiners to attend an actual operation with each candidate from across the country. This type of assessment would also be unethical since it would put a patient in the hands of a potentially very stressed surgeon. An objective assessment tool that is widely accessible could instead be used throughout training in order to facilitate improvement in technical skills and assessment of skills before becoming eligible to take final exams.

Trainees could learn to use an objective assessment tool like STAN throughout their training to track their performance on various procedures over time. Since the application has performance categories developed from multiple recordings with surgeons at various experience levels, trainees could objectively see when they are consistently achieving "expert" performance. The

app could serve to log much richer information than simply the number of cases done. Once expert performance is achieved on a defined set of procedures, the trainee would become eligible to take the licensing examinations. The performance-category specific feedback provided by STAN could facilitate and accelerate improvement in technical skills. The use of an objective assessment tool that includes specific feedback could also facilitate provision of more specific feedback from supervisors, which may serve to improve performance even further.

## References

1. Datta V., Mackay S., Mandelia M, Darzi A. (2001). The use of electromagnetic motion tracking analysis to objectively measure open surgical skill in the laboratory-based model. *J Am Coll Surg* Nov;193(5):479-85.
2. Grober, E. D., Roberts, M., Shin, E., Mahdi, M., & Bacal, V. (2010). Intraoperative assessment of technical skills on live patients using economy of hand motion: Establishing learning curves of surgical competence. *The American Journal of Surgery*, 199(1), 81-85.