Surgical Skill Level Classification Based on Surgical Tool Movements Using IMU Sensors

Yifeng Zhu[1], Peyman Benharash[2], Esteban Aguayo[2], Eunsuk Chong[3], Veronica Santos[3]

[1]*Dept. of Control Science and Engineering, Zhejiang University*
[2]*David Geffen School of Medicine, UCLA*
[3]*Dept. of Mechanical and Aerospace Engineering, UCLA*

BIOMECHATRONICS LAB at UCLA

CORE UCLA Cardiac Outcomes Research Laboratory

Background

Objective evaluation of surgical skills is important for training and assessment of the surgical community. Given the limited time and resources for medical education, a reliable system for autonomously evaluating skill level is needed.

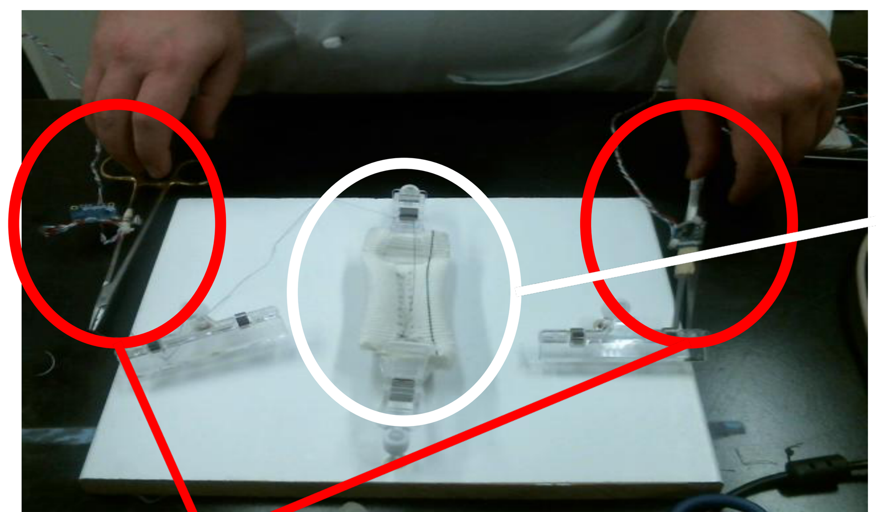
Our work aims to:

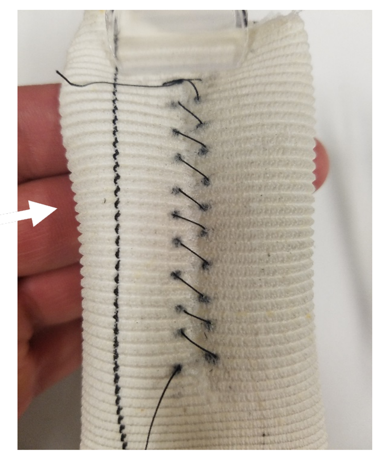
- Set up a low-cost data collection system
- Autonomously and objectively evaluate surgical skill level
- Characterize of experts' and novices' movements

Goal of this study:

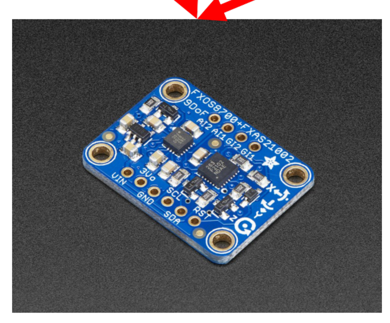
- Classify surgical skill level into expert and novice

Experimental Setting





Result of suturing



- One IMU on the needle driver
- One IMU on the forceps

Data from IMU

- Quaternion: (q_w, q_x, q_y, q_z)
- We convert quaternions into 3x3 rotation matrices, R
- Linear acceleration: (a_x, a_y, a_z)

Experimental set-up

- 9 degree-of-freedom inertial measurement unit (IMU sensor: Adafruit BNO055) attached to a needle driver and forceps

Task requirement:

- Suturing
- 10 stitches

Number of trials

Expert	Novice	Total
9	13	22

*Data were collected according to a UCLA IRB-approved protocol.

Methods and Results

Repetitive pattern of needle driver

1. Calculate change of "distance" between two rotation matrices[1]:

$$d_i = \left\|\ln(R_i R_0^T)\right\|, R_0 = I_{3\times3}$$

2. Normalize sequence $\{d_i\}$ by

$$n_i = \frac{2}{\max(\{d_i\}) - \min(\{d_i\})} d_i - 1, i = 1, 2, \dots L$$

3. *(Cross Correlation)* Obtain the repetitive pattern by

$$n_i' = \sum_{k=i}^{i+l} n_k \times n_{k-i+i_0}$$

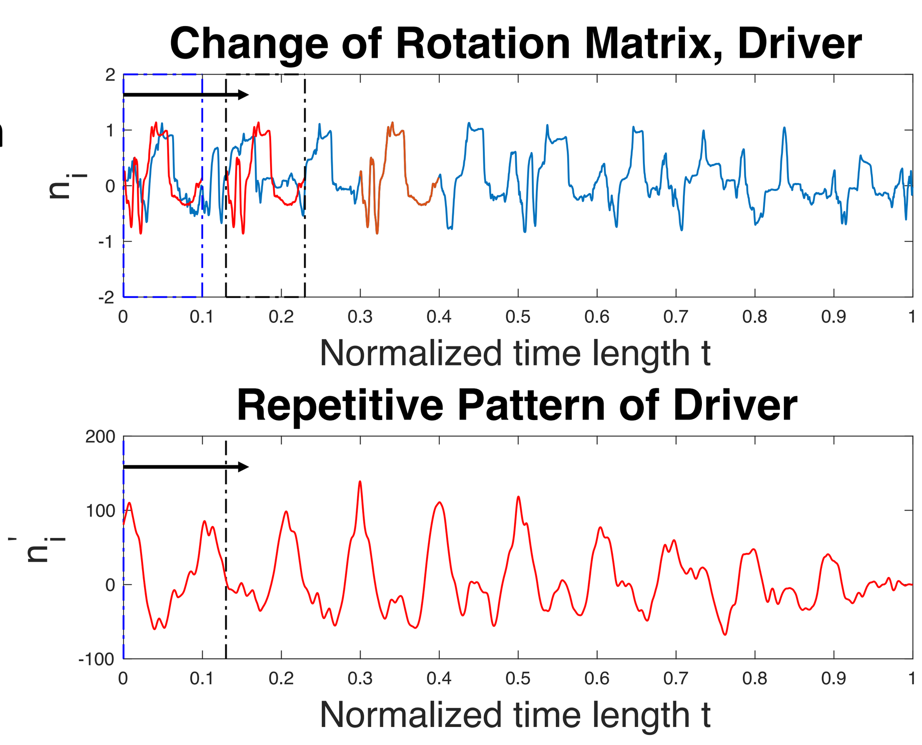
(with i_0 randomly chosen, $l = \frac{1}{10}L$)

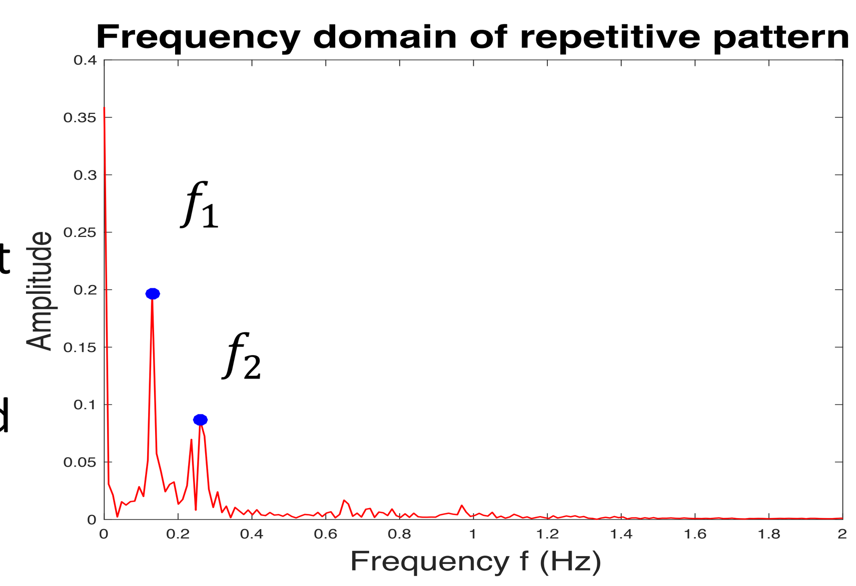
4. Frequency analysis of normalized repetitive pattern:

$$f = FFT(n')$$

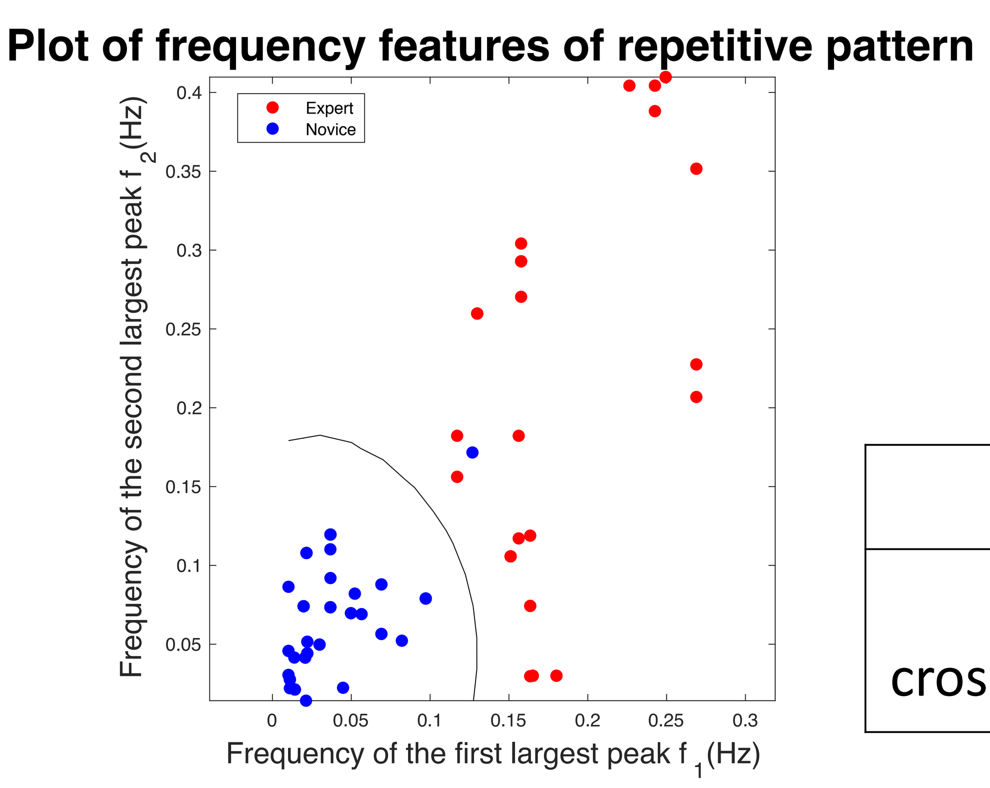
Choose frequencies f_1, f_2 corresponding to two largest peaks as features for all data.

5. Use Support Vector Machine[2] to classify data based on f_1 and f_2.





Brown curve: $\{n_k | k = i_0, i_0 + 1 \dots, i_0 + l\}$
Blue and black dashed line boxes: moving the segment selected (brown curve)



Classification based on needle driver

SVM	Gaussian Kernel
Leave-one-out cross validation accuracy	99.09%

Jerkiness of forceps

Jerkiness describes change of linear acceleration

1. Normalize time stamps into steps:

$$t_i' = \frac{t_i}{total\ time\ length}, i = 1, 2 \dots, L$$

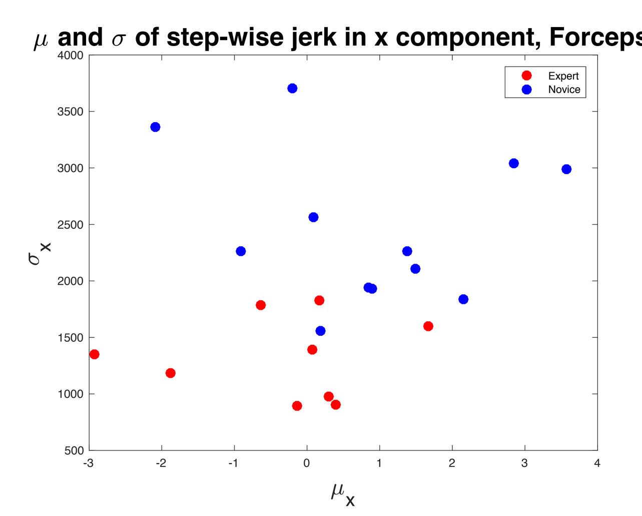
2. Calculate step-wise jerk:

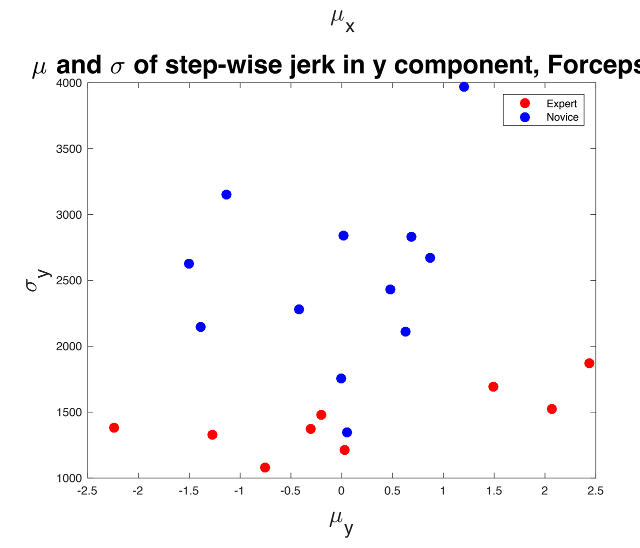
$$j_{x,i} = \frac{a_{x,t_{i+1}'} - a_{x,t_i'}}{t_{i+1}' - t_i'}, i = 1, 2 \dots, L-1$$

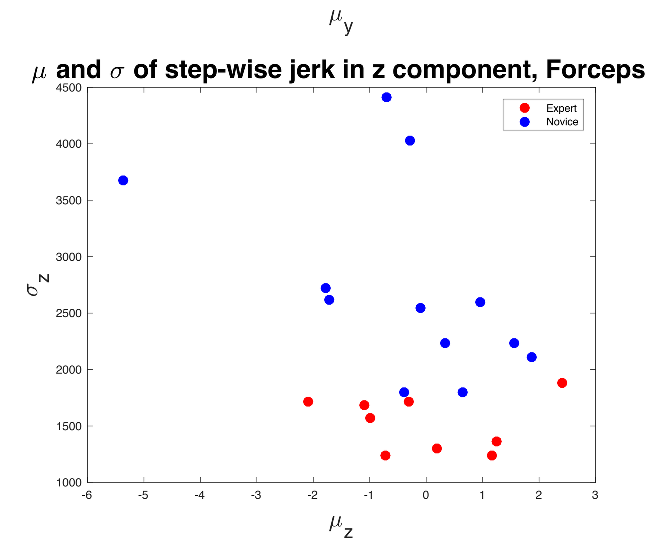
Obtain $j_{y,i}$, $j_{z,i}$ in the same way

3. Calculate mean value μ and standard deviation σ of $\{j_{x,i}\}$, $\{j_{y,i}\}$, $\{j_{z,i}\}$, which is denoted as $\mu_x, \sigma_x, \mu_y, \sigma_y, \mu_z$, and σ_z respectively. Take these six parameters from each data to plot figures on the right.

4. Classify data using SVM, and try four choices of features for classification.







Classification based on jerkiness of forceps

Features	Leave-one-out cross validation accuracy
$\sigma_x, \sigma_y, \sigma_z$	90.91%
μ_x, σ_x	77.27%
μ_y, σ_y	90.91%
μ_z, σ_z	90.91%

Conclusion

We have studied on features of surgical tool movements during suturing. Using only two IMU sensors for measuring surgical tool movements, our method shows meaningful results:

- Good classification accuracy of experts and novices
- Experts show significantly more repetitive pattern in using the needle driver
- Experts show smoother (less jerky) movements in using the forceps.
- Standard deviation is more useful than mean in analyzing jerkiness of forceps' movements

References

[1]Huynh, Du Q. "Metrics for 3D rotations: Comparison and analysis." *Journal of Mathematical Imaging and Vision* 35.2 (2009): 155-164
[2]Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning*, *20*(3), 273-297.

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