Advancing Remote Training Through a Flexible Glove for Real-Time Tracking and Analysis of Hand and Finger Movements

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I. Introduction

In recent years, remote training has gained significant attention since it offers the potential to bridge geographical distances and allow individuals to improve their skills remotely. However, one critical challenge in remote training lies in accurately tracking, analysing, and comparing complex hand and finger movements in real time, essential for providing precise feedback and facilitating skill development. Although potential applications of this technology encompass a wide range of fields, including music education, sports coaching, sign language detection, virtual reality gaming, and physical rehabilitation, this paper specifically focuses on applying flexible sensor gloves in surgical training.

Traditionally, the assessment of surgical technical skills for novice surgeons has relied on evaluations by expert surgeons. There are some limitations when expert surgeons observe the novice surgeon's skills and give feedback since it is difficult to have a direct line of sight and expert surgeons need to be physically present.

This research proposal aims to address this challenge by developing a cutting-edge solution as a flexible glove embedded with nine 9-axis Inertial Measurement Units (IMUs). The glove, equipped with sophisticated algorithms, will enable the real-time capture, analysis, and wireless transmission of hand movement data to an end device. A mobile application is used to give real-time feedback to surgeons.

The outcomes of this research can potentially transform the way training is conducted, transforming the remote learning landscape and allowing individuals to reach new levels of skill and proficiency.

II. Literature Review

In recent years, there has been growing interest in applying flexible gloves for real-time tracking and analysis of hand and finger movements in remote training. This has led to significant advancements in sign language recognition, physical rehabilitation, and surgical training. In particular, sensor gloves have emerged as a promising tool for tracking and analysing the skills of novice surgeons in both open and minimally invasive surgical procedures. These gloves can provide automated assessments with the help of artificial intelligence and machine learning algorithms. This literature review explores the application of flexible sensor gloves in the surgical field. It aims to critically analyse existing research on this topic, discussing the tracking indicators, performance analysis, human-machine interfacing, and statistical methods used in analysing.

A. Advances in Flexible sensor Glove Technology

Research into augmented gloves can be divided into vision-based and sensor-based approaches. Vision-based methods depend on externally mounted cameras capturing the entire hand, which poses challenges in interactions with objects or cluttered environments. Consequently, camera-based techniques are restricted to controlled environments and impose physical constraints on immersive user experiences. Mounting sensors directly onto the user's hand removes the need for direct line-of-sight and can improve reliability [2].

Sensor data gloves are electromechanical devices incorporated with a set of sensors, such as flex [3], optical, touch, tilt and magnetic sensors. These sensors were utilised to gather information on the finger tilt angle. However, many articles in literature take advantage of the flex sensor to acquire finger bend information. Motion tracking and hand orientation are other data acquired by the sensor. Three-axis accelerometer, six-axis inertial measurement unit (IMU) [4] and nine-axis IMU [2][5] were used for hand motion detection or orientation. The nine-axis IMU comprises a 3D accelerometer (ACC), 3D gyroscope (GYRO) and 3D magnetometer, which can measure acceleration, rate-of-turn and magnetic field, respectively.

TABLE I
SENSORS USED TO COLLECT DATA AND THE CORRESPONDING REFERENCES

Sensors	Advantages	Disadvantages	References
Inertial Measurement Units (IMU)	-High sample rate	-Cumulative error -Wired to provide power	[1][2][4][5] [13][18][20]
Optical markers	-Accuracy -Robustness (No dependence on objects in its environment) -Large Range -Wireless position markers	-Requires line of sight -Optical markers are relatively high	[19]
Flex sensors	-Low cost -Easy to use -Detects high range of bending angles	-Errors over time due to changes in sensor flexibility - Limitation of movement by wiring	[3][4]

B. Applications of Flexible Sensor Gloves in Remote Training

Numerous applications are currently involved in gesture recognition systems using sensor gloves, such as Sign Language Recognition, substitutional computer interfaces, socially assistive robotics, immersive gaming, virtual objects, remote control, medicine-health care, gesture recognition of hand/body language, etc.[6].

Among these applications, this paper specifically focuses on applying flexible sensor gloves in surgical training. The assessment of surgical technical skills are crucial for surgeons, whether in open surgery or less invasive techniques like robot-assisted laparoscopic surgery. Traditionally, the assessment of surgical skills depends on subjective methods such as direct observation and feedback from expert surgeons. This is time-consuming, non-scalable and inconsistent. Therefore, an automated system that can objectively identify the actual skills level of a junior trainee is highly desirable. [9]

Internet of Things (IoT) has opened up new possibilities in surgical training and assessment. IoT technologies enable the integration of sensors into surgical settings, providing real-time data that can be processed using artificial intelligence and machine learning algorithms. This data-driven approach is promising for enhancing surgical procedures in training and professional practice [10].

Simulators have proven effective in enhancing surgeons' skills outside the operating room (OR). However, their applicability is set back by the variability in requirements across different surgical techniques. Minimally invasive surgery (MIS), characterized by a limited workspace and restricted hand movements with four degrees of freedom (DoFs) due to fulcrum-mediated motion, has been more amenable to simulator-based training. On the other hand, open surgery (OS) involves a broader workspace and full DoF scenarios, making simulators less commonly accepted in this setting [4][8].

Sensor data Gloves have proven effective in remote monitoring and analysing hand movements in Open surgeries [8][3][4].

C. Human-Machine Interfacing

To ensure device usability, a simple management interface is useful to simplify the handling of the device. Real-time recognition providing a real-time response to a specific task in a recognition system is important in presenting immediate feedback to the user.

The most common way of providing feedback in surgical training is through visualisations. Trajectories, shown in 2D or 3D with different colours indicating sub-movements, are the most popular visualisation method. Other visualisations include bar charts displaying scores for various indicators and triangle radar charts depicting force parameters. However, these visualisations are often static, and further research is needed to explore how indicators evolve and determine the optimal number of training sessions required for improvement [10].

In control applications, gestures used for identification are typically categorised as static or dynamic. Static gestures are detected from a single image, while detecting gesture trajectories involves analysing multiple-image sequences. The Leap Motion device is commonly employed as a gesture-sensing device, integrated with the Unity game engine, which provides a suitable environment for setting up scenes and conducting gesture detection [11].

TABLE II
VISUALIZATION TYPES OF FEEDBACK MECHANISMS

Mechanisms	papers	References
Trajectories	5	[12][14][15][16]
Bar charts	1	[16]
Radar chart	1	[17]

D. Tracking indicators and Performance analysis

In surgical tracking, indicators can be categorised into five types: Position, Velocity, Acceleration, Orientation, and Force. These indicators provide information about the tools used by the surgeon and the movements of their body, with some indicators derived from position values, such as velocity and acceleration [10].

Regarding indicators related to the position, path length is the most common indicator used. Regarding indicators related to velocity, velocity values, understood as the path travelled on each of the three Cartesian axes at a given time (including mean, maximum value, minimum value or standard deviation), is the most common indicator used. Other indicators that have shown significant differences between the levels of expertise are the number of sub-movements obtained through velocity and spectral arc length obtained through the Fourier spectrum of velocity, and idle duration. To analyse the acceleration, changes in acceleration are the most common indicator used. Among the indicators related to orientation in surgical tracking, angular velocity, which measures the rotation angle on each of the three axes within a specific time period, is the most frequently employed indicator. Other indicators that have shown significant results are Angular path length, Orientation in three axes of rotation at different times. When it comes to indicators related to forces in surgical tracking, force values, which represent the force applied on each of the three Cartesian axes at a specific time (including metrics like maximum value, mean, median, deviation, root-mean-square, or total-sum-of-square), are the most frequently utilised indicators [10].

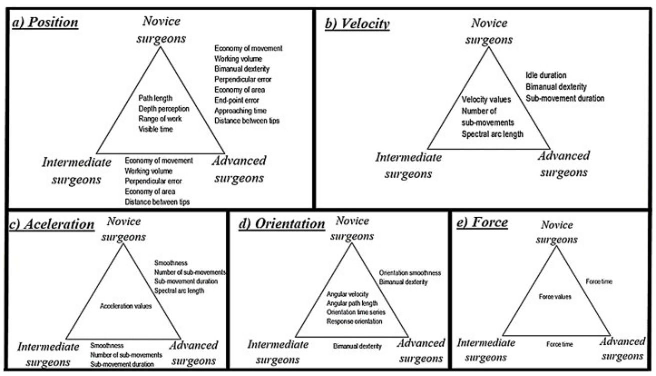

Fig. 1. Indicators with significant differences between levels of expertise (novice surgeons, intermediate surgeons and advanced surgeons): a) position; b) velocity; c) acceleration; d) orientation; and e) force. Those indicators that can be used to distinguish between the three levels of expertise are in the center of the corresponding triangle. Those indicators that can be used to distinguish between two levels of expertise are on the side of the corresponding triangle. Indicators for which no significant differences between levels of expertise were found are not shown in the corresponding triangle.

E. Statistical methods and algorithms used in comparison and analysis

The collected sensor data is processed using advanced statistical methods and machine learning algorithms for the objective and automated assessment of surgical technical skills. This processing serves two main purposes: classification of surgeons' expertise levels and prediction of scores. The data undergoes pre-processing steps such as feature extraction, normalisation, and selection. These steps help collect relevant data, reduce dimensionality, and eliminate noise. The focus of the article is on the application of statistical methods and algorithms rather than the specific details of data pre-processing [10].

Regarding classification, SVM (Support Vector Machine)[4][2][6], neural networks [4][6], discriminant analysis [6], Hidden Markov models [6], logistic regression, k-NN [6], Naïve Bayes, Random forest[5], and MLP(Multi-Layer Perceptrons) [5] are the most used statistical methods and algorithms used in classifying surgeon expertise levels. However, four main challenges can impact the accuracy of the results obtained. Challenges include the quality of input data, dataset dimensionality and feature selection, task dependency requiring exercise standardisation, and the influence of surgeon skills in training sets. At the same time, cross-validation may not precisely reflect real scenarios [10].

F. Conclusion

By accurately tracking and analysing hand and finger movements, sensor gloves enable real-time monitoring and feedback. The utilisation of machine learning algorithms allows the processing of data collected by these gloves to provide evaluations in surgical performances. However, challenges such as data quality, feature selection, exercise standardisation, and training set composition need to be addressed to improve the accuracy and applicability of these systems.

Although many researchers have focused on comparing the skill levels of surgeons in Minimally invasive surgery (MIS) like laparoscopic surgery, only few have focused on comparing the skills in Open surgery scenarios.

Another specific area that requires further attention is providing real-time feedback to users. While sensor gloves offer real-time monitoring capability, only a few articles have focused on developing methods for delivering instantaneous feedback to users. Exploring and developing techniques for providing timely and meaningful feedback will contribute to a more immersive and effective user experience.

References

[1] G. Arbelaez-Garces, D. Joseph, M. Camargo, N. Tran, L. Morel, "Contribution to the objective assessment of technical skills for surgery students: An accelerometer based approach," *International Journal of Industrial Ergonomics,* vol. 64, pp. 79-88, 2018

[2] O. Glauser, S. Wu, D. Panozzo, O. Hilliges, O. Sorkine-Hornung, "Interactive Hand Pose Estimation using a Stretch-Sensing Soft Glove", *ACM Transactions on Graphics,* vol. 38, issue 4, pp. 1–15, July 2019

[3] T. Zimmerman, J. Lanier, C. Blanchard, S. Bryson, Y. Harvill. "A hand gesture interface device," in *Conf. Human factors in computing systems,* ACM Sigchi Bulletin, 1986, pp.189-192.

[4] L. Sbernini, L. R. Quitadamo, F. Riillo, N. D. Lorenzo, A. L. Gaspari and G. Saggio, "Sensory-Glove-Based Open Surgery Skill Evaluation," in *IEEE Transactions on Human-Machine Systems,* vol. 48, no. 2, pp. 213-218, April 2018.

[5] C. Mummadi et al., "Real-Time and Embedded Detection of Hand Gestures with an IMU-Based Glove," *Informatics,* vol. 5, no. 2, p. 28, Jun. 2018.

[6] M. A. Ahmed, B. B. Zaidan, A. A. Zaidan, M. M. Salih, and M. M. bin Lakulu, "A Review on Systems-Based Sensory Gloves for Sign Language Recognition State of the Art between 2007 and 2017," *Sensors,* vol. 18, no. 7, p. 2208, Jul. 2018.

[7] P. Maceira-Elvira, T. Popa, A.C. Schmid, F.C. Hummel. "Wearable technology in stroke rehabilitation: towards improved diagnosis and treatment of upper-limb motor impairment," *J NeuroEngineering Rehabil,* Nov 2019.

[8] B. Genovese, S. Yin, S. Sareh, M. DeVirgilio, L. Mukdad, J. Davis, V.J. Santos, P. Benharash. "Surgical Hand Tracking in Open Surgery Using a Versatile Motion Sensing System: Are We There Yet?," in *The American Surgeon,* 2016, pp.872 - 875.

[9] X.A. Nguyen, D. Ljuhar, M. Pacilli, R.M. Nataraja, S. Chauhan, "Surgical skill levels: Classification and analysis using deep neural network model and motion signals," *Computer Methods and Programs in Biomedicine,* vol. 177, pp. 1-8, 2019.

[10] P. Castillo-Segura, C. Fernández-Panadero, C. Alario-Hoyos , P.J. Muñoz-Merino, C.D. Kloos, “Objective and automated assessment of surgical technical skills with IoT systems: A systematic literature review,” *Artif Intell Med.,* vol.112, 2021

[11] C. -C. Tsai, C. -C. Kuo and Y. -L. Chen, ”3D Hand Gesture Recognition for Drone Control in Unity,” *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE),* Hong Kong, China, 2020, pp. 985-988

[12] G. Forestier, F. Petitjean, P. Senin, F. Despinoy, P. Jannin, (2017, June). “Discovering discriminative and interpretable patterns for surgical motion analysis,” in *Conference on Artificial Intelligence in Medicine in Europe,* Springer, Cham, (pp. 136-145).

[13] M. Levin, T. McKechnie, S. Khalid, T.P. Grantcharov, M. Goldenberg, ”Automated Methods of Technical Skill Assessment in Surgery: A Systematic Review,” *Journal of Surgical Education,* vol. 76, issue 6, pp. 1629-1639, 2019.

[14] H.I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, P.A. Muller, “Evaluating surgical skills from kinematic data using convolutional neural networks,” in *International Conference on Medical Image Computing and Computer-Assisted Intervention,* Springer, Cham, 2018, pp. 214-221.

[15] M. Uemura, M. Tomikawa, R. Kumashiro, T. Miao, R. Souzaki, S. Ieiri, K. Ohuchida, A.T. Lefor, M. Hashizume, “Analysis of hand motion differentiates expert and novice surgeons,” *Journal of surgical research,* vol. 188, issue 1, pp. 8-13, 2014

[16] M. Uemura, M. Tomikawa, T. Miao, R. Souzaki, S. Ieiri, T. Akahoshi, A.K. Lefor, M. Hashizume, “Feasibility of an AI-Based measure of the hand motions of expert and novice surgeons,” *Computational and mathematical methods in medicine,* pp.1-6, Mar 2018.

[17] T. Sugiyama, S. Lama, L.S. Gan, Y. Maddahi, K. Zareinia, G.R. Sutherland, “Forces of tool-tissue interaction to assess surgical skill level,” *JAMA surgery,* vol. 153, issue 3, pp. 234-242, 2017

[18] M. Ershad, R. Rege, A.M. Fey, “Meaningful assessment of robotic surgical style using the wisdom of crowds,” *International journal of computer assisted radiology and surgery,* vol. 13, issue 7, pp. 1037-1048, Jul 2018.

[19] A.L.D. D’Angelo, D.N. Rutherford, R.D. Ray, S. Laufer, C. Kwan, E.R. Cohen, A. Mason, C.M. Pugh, “Idle time: an underdeveloped performance metric for assessing surgical skill,” *The American Journal of Surgery,* vol.209, issue 4, pp. 645-651, 2015.

[20] X.A. Nguyen, D. Ljuhar, M. Pacilli, R.M. Nataraja, S. Chauhan, “Surgical skill levels: Classification and analysis using deep neural network model and motion signals,” *Computer methods and programs in biomedicine,* vol. 177, pp. 1-8, Aug 2019.