SURGICAL SKILL EVALUATION BY MEANS OF A SENSORY GLOVE AND A NEURAL NETWORK

Giovanni Costinini[1], Giovanni Saggio[1], Laura Sbernini[1], Franco Di Paolo[1], Daniele Casali[1]

[1]Dept. of Electronic Engineering, University of Rome Tor Vergata, Via del Politecnico 1, 00133 Rome, Italy,
e-mail costantini@uniroma2.it

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One of the most important skills of a surgeon is the ability to perform hand motion tasks with precision, accuracy, and firmness. Indeed, these tasks cannot be trivial since the necessity of adaptation to every single situation, being the context never absolutely identical. However, an experienced surgeon is able to repeat as many tasks as required, always maintaining similar precision and accuracy, especially in some key-phases of the gesture. This cannot be the same for novice surgeons still on the learning curve, as already demonstrated in robotic surgical system by means of pattern of movements [1,2], in laparoscopic surgery by means of eye patterns [3], and in simulation-based training by means of video analysis [4].

In such a frame, an automatic system, able to analyze the hand gestures and classify their effectiveness, can be strategically adopted. This system can objectively evaluate the performance of an apprentice surgeon and time tracing his/her progresses. Moreover, gesture recognition is a well-known topic of machine learning and it has been mostly studied for sign language recognition [5].

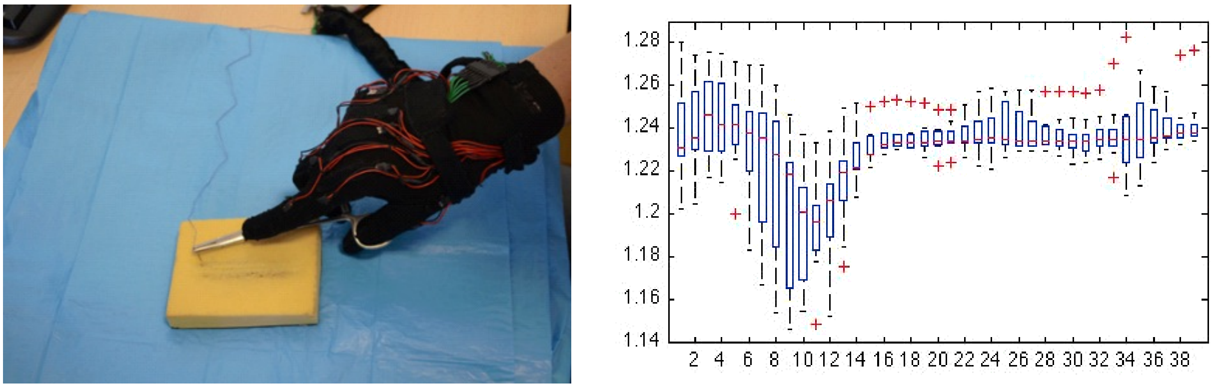
Our works intends to propose a system to evaluate surgical skills, by means of measuring system based on a sensory glove, and a classification method based on Neural Network. It compares hand motion tasks performed both by expert than novice surgeons. Our sensory glove (Fig. 1), termed Hiteg-glove, is made of a supporting glove with 20 embedded sensors, including bending types, 3D accelerometers and 3D gyroscopes [6,7]. The glove includes 20 sensors: two bending sensors are for the thumb (1-2), three for the other fingers (3-14), and three accelerometers (15-17) plus three gyroscopes (18-20) are for the wrist. The bending sensors measure Distal Interpahlangeal (DIP), Proximal Interphalangeal, and Metacarpo Phalangeal angles, while the inertial units measures wrist movements.

For the training of the system, each subject is asked to repeat the gesture in a given number of times. The system first performs a pre-processing, where data is filtered with a moving average filter. Information regarding the actual duration of the gesture is taken into account separately.

Data coming from the 20 sensors are splitted into windows of 50 samples, obtaining 39 windows in total. Every window is a representation of the state of the system in a specific interval of time. For every window we calculate the mean value of its samples; the obtained value is averaged over the n repetitions. As an example, Fig. 2 reports data from sensor 20 (gyroscope, axis z) in a box-plot. In the axis x we reported the time window (1-39), in axis y the values from of expert subjects. On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually.

With 20 sensors and 39 time-series values, we have a total of 780 values that can be considered as features for classification. In addition, we also consider the median value of the time length of the gesture. For the classification, we used an Artificial Neural Network (ANN) being the hidden layer made up with 4 neurons on, since we noticed worse results with a lower number, and no improvements with a higher number. To reduce the number of feature we applied the Correlation-based Feature Subset Selection (CFS) algorithm [8], where only features that have higher correlation with the class and lower correlation among themselves are chosen.

We tested the system with a set of 18 subjects: 9 of them were skilled surgeons and 9 novices on their starting learning curve. All of them were asked to perform the same task: a suture on a plastic material designed to have the same characteristics of human skin. Two sessions were performed. Every subject, at every session, repeated the gesture 10 times. We performed a cross-validation of the system. The dataset was randomly partitioned in 6 groups called "folds": a single fold was used as validation set while the remaining 5 as training set. The process was repeated 6 times, with each 6 folds used exactly once as the validation set. Finally, the 6 results were combined together. The result is that 94.4% of the instances are correctly classified, while 5.6% are incorrectly classified.



a) b)

Fig. 1: a) The HITEG data glove during the experiment
b) Box-plot of sensor 20, for all experts, from time window 1 to 39 (begin to end of every repetition).

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