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Skill Assessment Using Kinematic Signatures: Geomagic Touch Haptic Device

N. S. Hojati*, M. Motaharifar*, H. D. Taghirad*, A. Malekzadeh+
*Advanced Robotics and Automated Systems (ARAS), Industrial Control Center of Excellence (ICCE),
Faculty of Electrical Engineering, K.N. Toosi University of Technology, Tehran, Iran.
Email: negarhojati@email.kntu.ac.ir, motaharifar@email.kntu.ac.ir, taghirad@kntu.ac.ir
+Faculty of Mathematics, K.N. Toosi University of Technology, Tehran, Iran. Email: malekzadeh@kntu.ac.ir

Abstract—The aim of this paper is to develop a practical skill assessment for some designed experimental tasks, retrieved from Minimally Invasive Surgery. The skill evaluation is very important in surgery training, especially in MIS. Most of the previous studies for skill assessment methods are limited in the Hidden Markov Model and some frequency transforms, such as Discrete Fourier transform, Discrete Cosine Transform and etc. In this paper, some features have been extracted from time-frequency analysis with the Discrete Wavelet Transform and temporal signal analysis of some kinematic metrics which were computed from Geomagic Touch kinematic data. In addition, the k-nearest neighbors classifier are employed to detect skill level based on extracted features. Through cross-validation results, it is demonstrated that the proposed methodology has appropriate accuracy in skill level detection.

Index Terms—Robotics-Assisted Minimally Invasive Surgery, skill assessment, feature extraction, time-frequency analysis, temporal signal analysis.

I. Introduction

Assessment of surgical skills during the training process of novice surgeons is an essential part of Minimally Invasive Surgery (MIS). MIS is a kind of surgical technique in which surgical instruments are inserted through small incisions. This surgical procedure needs a new set of skills for a surgeon to perform MIS's techniques. Therefore, there is a need for a new training and assessment mechanism to evaluate novice surgeon before entering the operating room [1].

Global rating scales (GRS) and Objective Structured Assessment of Technical Skill (OSATS), which is a combination of GRS and checklists are standard practical skill assessment methods. They are currently in use in medical education [2]. OSATS includes 9 metrics such as respect of tissue, time and motion, instrument handling, and etc. In surgical skill assessment through OSATS, the expert supervises the surgical procedure with a camera and determines the score of each metrics for each trainee. In the end, the total score of the GRS and the checklist is presented as the final grade of the trainee. These performance metrics and the method of scoring is still subjective [3], in the sense that it just depends on the result of surgery; it is time-consuming and there is no feedback during learning complex tasks [4], [5].

Using haptic devices in surgical training and assessment is a new attitude in this branch of medicine. Haptic devices involve physical contact between computer and user, usually through an input/output device, such as a joystick or data gloves. Haptic devices highly facilitate surgical training on account of the fact that they provide an appropriate perception of the surgical environment for novice surgeons. Furthermore, the capability of recording position and force signals make haptic technology suitable for skill assessment, especially in MIS. By increasing the amount of Robot-Assisted Minimally Invasive Surgery (RAMIS) around the world, applying RAMIS in surgical training and surgical skill assessment has been noticed [6], [7]. RAMIS makes enable to drive position-based and force-based metrics from the recorded data to obtain a quantitative and automatic scoring system [8]–[10].

Recent approaches for automated surgical skill assessment are based on Hidden Markov Model (HMM) [11] and applying classification methods to global movement features [12]. Recommended feature extraction methods in previous works are Sequential Motion Texture (SMT), Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and Approximate Entropy (ApEn) [13] that do not contain local information about the movement. Performing linear discriminant analysis with cross-validation to examine the correlation between the skill level and the selected metrics is another effort in this context [14]. According to the results mentioned in [14], this method has less accuracy to detect different skill levels.

Although the above studies investigated key novel concepts in skill assessment, none of them have noticed to discrete wavelet time-frequency analysis. The most important superiority of wavelet transform to Fourier transform is that it provides the possibility of simple analyzing intense and abrupt behaviors in hand movement [15]. Therefore, it is inferred that the discrete wavelet transform is an appropriate method for recognizing the motion pattern of people with different skill level.

This investigation presents an automated skill assessment method based on kinematic metrics that pursue the progress of individuals in simple tasks. For this purpose, a sensorimotor task station is designed using the Geomagic Touch haptic device, and classification analysis on the extracted features from kinematic metrics is employed. To determine how well they could predict the practical skill progression process, k-nearest neighbors (KNN) classifier is employed.

The rest of the paper is organized as follows. The methods for data analyzing described in Section II. Section III presents our experimental setup and modules. The result of the classifier based on selected features is presented in Section IV. Finally, the paper ends up with conclusion in Section V.

II. METHODS

A. Data analyzing

In order to have a quantitative assessment of practical skill, some kinematic metrics are employed, including the tool position at any moment, tool-tip speed, acceleration magnitude and, jerk.

Our overall strategy is to consider some features, based on Discrete Wavelet Transform (DWT) coefficients of computed metrics to classify the skill level during the training process. Based on experiments performed at each module, from the first set of each participant we chose one or more tests as a novice. From second and third sets, some tests were taken as an intermediate and from the fourth set of each participant, one or more tests selected as an expert. Study the results of experiments show that most of the participants after four or five test sets, obtain proper ability to do the tasks with their non-dominant hand.

Temporal signal analysis: Straight line path and circle path are examined in two different methods of temporal analysis, which are described respectively. In straight line path Mean Square Error (MSE) is calculated in N windows that first, we divide recorded X and Y to N windows, as well as X_r. Next, the mean of each window of X, Y, and X_r is computed ($\bar{X}$, $\bar{Y}$and$\bar{X}_r$) which by placing $\bar{X}$ in the line equation and calculation the essential Y (Y_E), MSE is computed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_E - \bar{Y})^2 \tag{1}$$

where N is the number of windows, Y_E figures out from placing $\bar{X}$ in the line equation and $\bar{Y}$ is the vector of the average of each window of Y.

Computing MSE based on the mentioned method depends on the number of windows. It is important to choose the proper N due to the number of data samples.

Calculating MSE for circle path is different from the straight line. Therefore, this research proposes a new approach named Accumulated Distances of Nearest Points (ADNP), based on finding the nearest point of the circle to the mean of each window. Same as given above, divide X and Y to N windows and then mean of each window is computed. The nearest point of the circle to each mean is found and finally, all distances are accumulated. MSE with divide data to N windows and ADNP have two important advantages. The most important one is that regardless of speed variation in path traverse, they can find the positional difference between the participant's location and the desired point. Another one is that these methods provide the possibility of comparison of two paths with different time duration. In ADNP, the type of path is not important accordingly this method can be implemented for each curved path.

Discrete wavelet transform: The most important superiority of wavelet transform to Fourier transform is that it provides the possibility of non-stationary signal components analysis. While wavelet analysis offers simultaneous localization in time and frequency domain, classical Fourier transform of a signal does not contain local information of data. One of the most important objectives of extending the wavelet transform is analyzing the seismic behavior in a short period of a signal [15]. Therefore, it seems that the wavelet transform is an excellent choice for our problem because participants have a tremor in their hands, especially in the early stages of training. Discrete wavelet transform has been used in heart disease classification to classify between normal and abnormal heart [16] and more applications in image data processing like texture classification by image data [17], classification of magnetic resonance images of the human brain as either normal or abnormal [18]. Accordingly, we suggest DWT as an efficient method to extract fundamental features from an unfamiliar behavior.

With several derivations of recorded X and Y, other kinematic metrics such as speed, acceleration magnitude, and jerk are computed. Haar wavelet transforms in 4 levels for each metric is computed, which for the inclusive processing all have been taken. Haar wavelet is a sequence of square-shaped functions that together form a wavelet family. From each level of a DWT, some features such as mean, variance, mean of energy, maximum energy and, the maximum amplitude have been extracted from the coefficients vector which we consider mean of each feature among four levels.

Feature extraction, preprocessing and classification: The features listed above are calculated as follows:
Mean: Average value of each coefficients vector

$$M = \frac{1}{n}\sum_{i=1}^{n}(x_i) \tag{2}$$

where n is number of samples and x is data sequence.
Variance: Variance is computed by averaging the sum of square distance of observed value from the mean

$$V = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - M)^2 \tag{3}$$

Mean of energy: The Energy of a signal defined as the sum of the square signal. Mean of energy is the average of energy.

$$M_e = \frac{1}{n}\sum_{i=1}^{n} x_i^2 \tag{4}$$

Maximum energy: It is the highest value of the energy vector.
Maximum amplitude: It is the peak value of the x sequence.

Altogether, 21 features are extracted from DWT coefficients of three metrics (tool position, speed of tool-tip, acceleration magnitude and, jerk). Notably, all of the extracted features are not essential for classification and it is necessary to eliminate the redundant features before passing them onto the classifier. In order to estimate the optimum amount of features, performance of the classifier with different features is evaluated. Finally, the ones that have the highest average performance of classifying respective task are picked up.

We use a simple k-nearest neighbor (KNN) to classify skill level based on extracted features. In order to prove the correctness and accuracy of the classifier, the k-fold cross-validation setup is employed.

III. EXPERIMENTAL SETUP

The experiments were performed at ARAS lab, Faculty of Electrical Engineering, K. N. Toosi University of Technology. The participants were members of ARAS lab, Postgraduate and Ph.D. students (three females and four males) in the age between 23 to 30. Except for two participants, the rest were right-handed.

At the beginning of the tests procedures, both experiment modules were explained for participants and they were asked to take part in experiments several days. In each set of tests, both modules were tested for five times. To better see the progression process, participants were asked to do all tasks with their non-dominant hand. Our experimental setup consists of a Geomagic Touch haptic device, a plate which placed exactly in front of the haptic device that was fixed by shields and, a monitor to see the cursor relative to the handle of the haptic device, see Fig. 1.

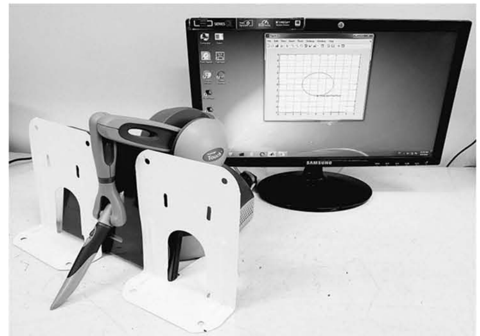


Fig. 1: The Experimental setup with Geomagic Touch haptic device.

The Geomagic Touch system provides realistic 3D Touch sensation for any application. Its workspace is $160W \times 120H \times 70Dmm$. Its position sensing has 6 degrees of freedom, $x, y, andz$ through digital encoders and Roll, pitch, yaw by linearity potentiometers [19].

Module_1: For the path traversing, there were two paths with a distinct starting point and endpoint. Participants were asked to find the cursor related to the haptic handle on the x-y plane. Let us define the coordinates of the workspace, with horizontal (X-axis), vertical (Y-axis), depth (Z-axis) components. The location of starting point and endpoint for a straight-line path were at (0,-10,0) and (4,10,0), respectively. The circular path was started and ended at (0,-2,0) with a radius of two units. In the circle path, all participants started with the right side movement.

Module_2: The goal is to prepare an unfamiliar environment in which participants must rapidly adapt with variable opponent force. The presence of an opponent force in the half of the path led to instrument vibration in the entry point. Through this module, participants learned how to control the instrument vibration in entry point and adapt with variable opponent force. This module is analogous to what would occur when the surgeon wants to insert the instrument into the tissue. The circular path was as the same as Module_1 but with the different starting point and endpoint (-2,-25,0). The opponent force was applied along the x-axis, toward the outside of the left semicircle. Matlab sample rate was chosen $0.001s$ in both modules.

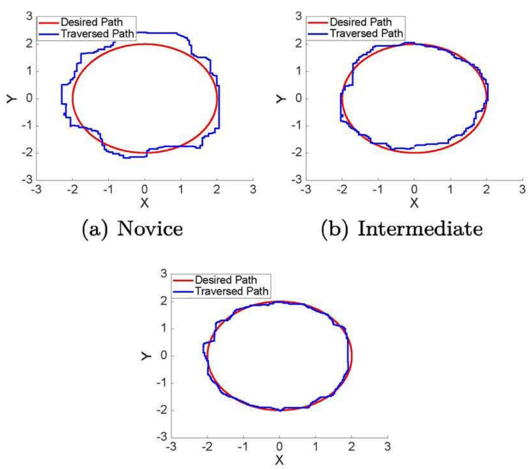
IV. RESULTS

Fig 2 is a sample of selected tests as the novice, the intermediate and the expert. Desired path is illustrated with red color and traversed path with blue. Fig 2 (a) is a selected test from first set, Fig 2 (b) is from second set and Fig 2 (c) is from fourth set of experiment test of a left hand participant.

We observed that as the number of windows increases, MSE and ADNP converge to their original value. We have concluded from MSE and ADNP calculation that with the sample rate of $0.001s$, the most appropriate number of windows is between 100 to 150. However, if the sample rate is lower, the number of windows is reduced.

Figs. 3 and 4 show subplot results of some of the thirteen extracted features from straight-line path and nine extracted features from circle path in Moduel_1. As can be seen in both figures, there is a significant difference between the result of each feature and skill levels, in the sense that these features can discern the skill level properly. Fig. 5 shows five extracted features from the circle path in an unfamiliar environment with opponent force (Moduel_2). Features are mean, variance, mean of energy, maximum energy and maximum amplitude of discrete wavelet transform of kinematic metrics. In these figures index of each caption refers to related metric.

Selected features were employed in KNN classifier in order to distinguish skill level. In Moduel_1, the classifier has 0% k-fold loss for straight-line path and 16% k-fold loss for circle path. In Moduel_2, circle path with opponent force has just 12% k-fold loss in skill level detection. Because the extracted features from DWT coefficients carry important signatures of hand movement, the loss of classifier reduced significantly. Considering time-frequency analysis with DWT and temporal signal analysis together is another important aspect of this study. It is also inferred that whatever the tasks become complex, fewer features are needed to distinguish skill level. The common features in both modules are the maximum amplitude of speed, the maximum energy of speed, the maximum energy of jerk, ADNP in the circle path and MSE in the straight line. Therefore, the mentioned features are the most important ones in simple and complex task skill level detection.



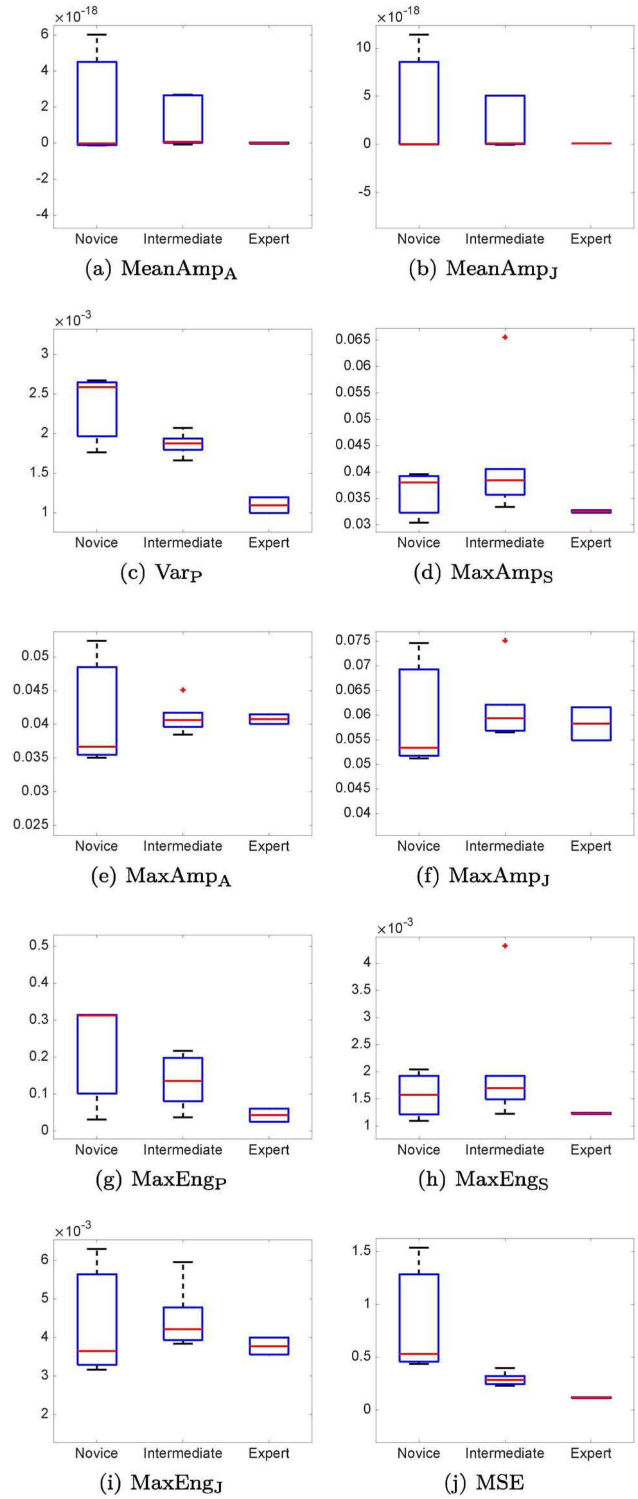
(a) Novice (b) Intermediate

(c) Expert

Fig. 2: Examples of novice, intermediate, and expert experimental results (Module_1).

V. CONCLUSIONS

In this paper, a skill level detection method is proposed for a sensorimotor designed task. The suggested method is based on time-frequency analysis with discrete wavelet transform and temporal signal analysis. Some extracted features from DWT coefficients are chosen and applied to KNN classifier. Cross-validation results show the effectiveness of the proposed approach. Our future work is to develop a generalized method of skill assessment which is able to score practical skills in more accurate levels for developed experimental test scenarios of MIS. In addition, applying our proposed method on clinical experimental test is our another goal.



(a) $\mathrm{MeanAmp_A}$ (b) $\mathrm{MeanAmp_J}$

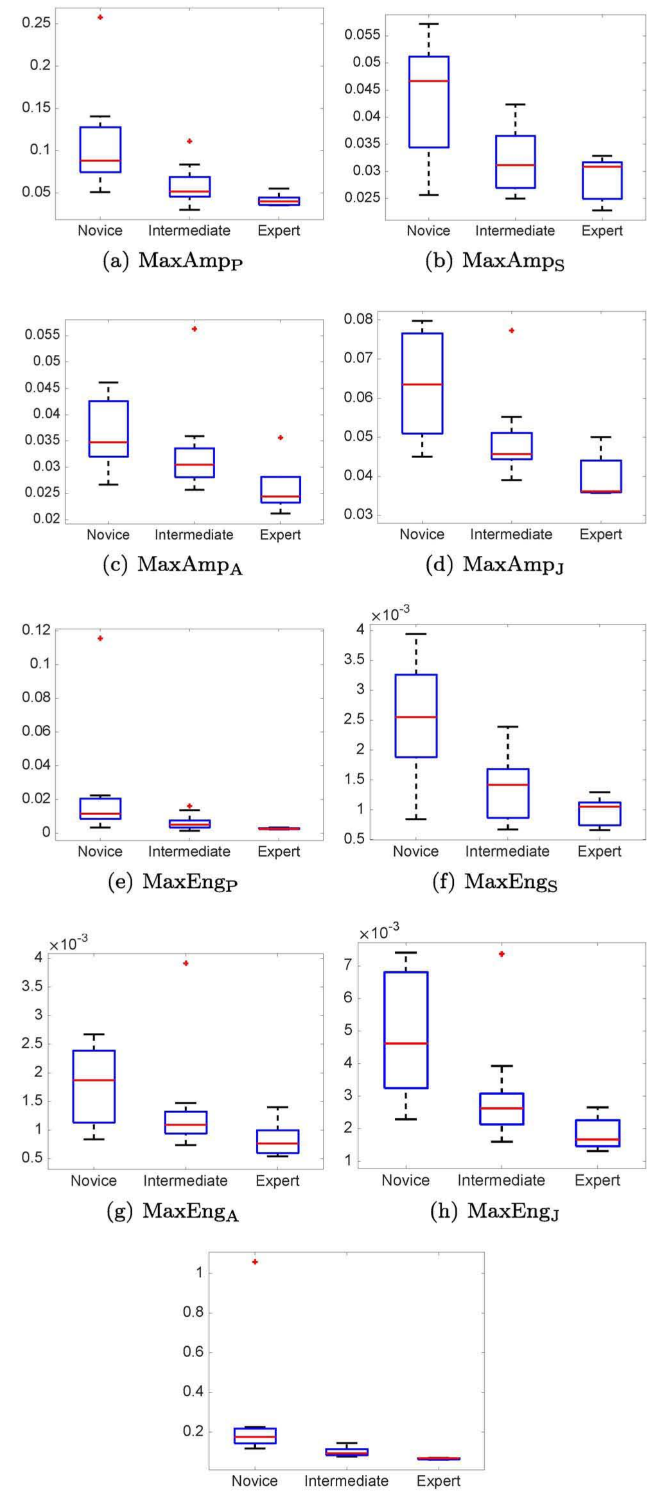
(c) $\mathrm{Var_P}$ (d) $\mathrm{MaxAmp_S}$

(e) $\mathrm{MaxAmp_A}$ (f) $\mathrm{MaxAmp_J}$

(g) $\mathrm{MaxEng_P}$ (h) $\mathrm{MaxEng_S}$

(i) $\mathrm{MaxEng_J}$ (j) MSE

Fig. 3: Selected features from the straight-line path test (Moduel_1).



(a) $\mathrm{MaxAmp}_{\mathrm{P}}$ (b) $\mathrm{MaxAmp}_{\mathrm{S}}$

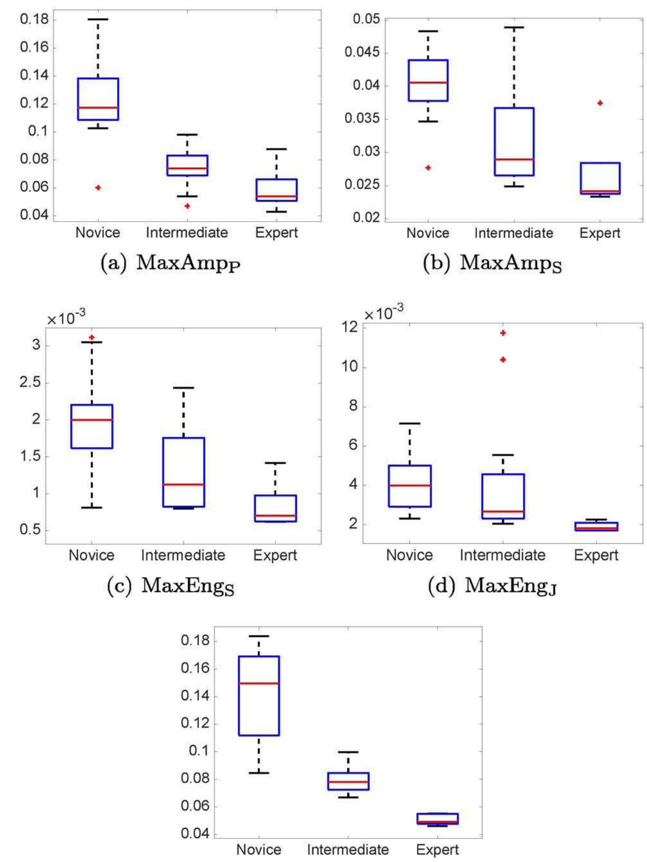
(c) $\mathrm{MaxAmp}_{\mathrm{A}}$ (d) $\mathrm{MaxAmp}_{\mathrm{J}}$

(e) $\mathrm{MaxEng}_{\mathrm{P}}$ (f) $\mathrm{MaxEng}_{\mathrm{S}}$

(g) $\mathrm{MaxEng}_{\mathrm{A}}$ (h) $\mathrm{MaxEng}_{\mathrm{J}}$

(i) ADNP

Fig. 4: Selected features from the circle path test (Moduel_1).



(a) $\mathrm{MaxAmp}_{\mathrm{P}}$ (b) $\mathrm{MaxAmp}_{\mathrm{S}}$

(c) $\mathrm{MaxEng}_{\mathrm{S}}$ (d) $\mathrm{MaxEng}_{\mathrm{J}}$

(e) ADNP

Fig. 5: Selected features from Moduel_2 experimental test.

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