SATR-DL: Improving Surgical Skill Assessment and Task Recognition in Robot-assisted Surgery with Deep Neural Networks

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Abstract—Purpose: This paper focuses on an automated analysis of surgical motion profiles for objective skill assessment and task recognition in robot-assisted surgery. Existing techniques heavily rely on conventional statistic measures or shallow modelings based on hand-engineered features and gesture segmentation. Such developments require significant expert knowledge, are prone to errors, and are less efficient in online adaptive training systems. Methods: In this work, we present an efficient analytic framework with a parallel deep learning architecture, SATR-DL, to assess trainee expertise and recognize surgical training activity. Through an end-to-end learning technique, abstract information of spatial representations and temporal dynamics is jointly obtained directly from raw motion sequences. Results: By leveraging a shared high-level representation learning, the resulting model is successful in the recognition of trainee skills and surgical tasks, suturing, needle-passing, and knot-tying. Meanwhile, we explore the use of ensemble in classification at the trial level, where the SATR-DL outperforms state-of-the-art performance by achieving accuracies of 0.960 and 1.000 in skill assessment and task recognition, respectively. Conclusion: This study highlights the potential of SATR-DL to provide improvements for an efficient data-driven assessment in intelligent robotic surgery.

I. INTRODUCTION

In robot-assisted minimally-invasive surgery, surgeon expertise directly affects overall surgical performance and patient safety. Technical training programs are necessary to ensure trainees develop adequate skills to teleoperate robots and perform complex operations proficiently. Due to the steep learning curves, an objective measure of trainee performance and automated identification of surgical activity are of prominent concerns towards an efficient training and intelligent robot autonomy in order to further enhance surgery outcomes [1], [2].

Current techniques for objective surgical skill assessment include descriptive statistics (time, path length, smoothness, etc.) [3], [4], gesture segmentation-based analysis such as Hidden Markov Models (HMM) [5], and feature-based modelings such as k-nearest neighbor (kNN), support vector machine (SVM) [6]. Given an observation of motion data from robot end-effectors, local segmented gestures or hand-crafted features are extracted and fed into a classifier to assess trainee skills and performance. Similarly, these techniques are applied to understand underlying surgical task structures and workflow [7]. However, the aforementioned approaches are limited in several ways. First, it is time-consuming and strenuous to manually design meaningful representations to uncover hidden patterns of complex motion. Gesture segmentation is task-dependent, limited to specific operations and requires significant prior knowledge of particular structures and pre-processing to decompose motion sequences. Moreover, a common deficiency is that most classifications can only obtained at the level of trial, which requires an entire observation of each training operation. These drawbacks make previous approaches less efficient for an online automatic feedback system. A sequence distance-based method, such as dynamic time warping (DTW), has been proposed to provide feasible online classifying for surgical task and gesture recognition [8]. However, higher computational loads involved in practice, as well as the role of DTW in the skill analysis still remains unknown.

In this paper, we aim at developing an end-to-end surgery motion analytic framework based on a multi-output deep learning architecture, SATR-DL, for online trainee skill analysis and task recognition (Figure 1). In particular, by integrating a Convolutional Neural Network (CNN) [9] and Gated Recurrent Unit (GRU) network [10], our proposed deep model can simultaneously learn both spatial (convolutional) abstract representations within the interval of input frame, as well as the temporal dynamics of multiple channels at each time step in raw motion data. By exploring these intrinsic properties of kinematic sequences, SATR-DL can effectively characterize the nature of surgery motion relative to both the trainee experience and operation activity. Crucially, this work does not assume any prior knowledge of primitive gestures and does not require pre-defined features. We find that our SATR-DL significantly enhances both the efficiency and accuracy when compared to other techniques in the study of robotic surgery assessment.

II. METHODOLOGY

A. Problem Formulation

The goal of the SATR-DL model is to directly map raw motion kinematics onto labels of trainee skills and corresponding training tasks. This can be formalized as a supervised classification problem with multiple outputs, given a time interval of high-dimension motion sequences as input, \( X \in \mathbb{R}^{T \times C} \). Here, \( T \) refers to the time steps in each interval frame and \( C \) is the number of channels of the input. The outputs are label \( y_1 \in \{1 : “novice”, 2 : “intermediate”, 3 : “expert”\} \) for skill levels, and label \( y_2 \in \{1 : “suturing”, 2 : “needle-passing”, 3 : “knot-tying”\} \) for training tasks. We take the jointed cross-entropy loss as the global objective function (Eq. 1), which measures the total discrepancy between the ground-truth and predicted labels of two outputs.

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J(\theta) = - \sum_{i=1}^{l} \sum_{t=1}^{m} \sum_{k=1}^{K} \log p(y^{i}_j = k | x^{(i)}; \theta) 
\] (1)
where \( l \) is the total output number (\( l = 2 \) for skill and task classification), \( m \) is the number of training examples, \( K \) is the total label number for each output (\( K = 3 \)), and \( p(y^{(i)}_j = k | x^{(i)}; \theta) \) is the conditional likelihood that the predicted label \( y^{(i)}_j \) of output \( j \) on a single example \( x^{(i)} \) assigns to the \( k \)-th label, given the trained model parameters \( \theta \).

The classification is conducted for each time interval frame (every 4 seconds). In addition, for trial-level assessment, a majority voting is used on the whole trial sequence based on the ensemble of interval-level classification in order to deliver a robust classification performance.

### B. Overall Architecture

Figure 2 shows the design of our SATR-DL model. The proposed architecture is composed of a temporal component that decodes temporal information across each time step and a convolutional component that explores implicit representations over spatial (convolutional) dimensions in the input frame. Specifically, the convolutional component consists of two stacked basic blocks with kernel numbers of 32 and 64, respectively. Each block consists of a convolution layer with 1-D kernel of size 2, followed by a batch normalization (BN) [11], a rectified linear unit (ReLU) activation [12], and a dropout layer (dropout rate 0.2) [13]. In parallel, two stacked GRU recurrent neural networks are applied to process the input for learning temporal dynamics of motion sequences. The hidden units for the first and second GRU layers are set as 128 and 64, respectively. A dropout with the probability of 0.2 is applied after each GRU layer. The output of convolutional block with flattening and the 2-layer GRU are reconstructed by a concatenation component, followed by a batch normalization, ReLU activation and a dropout with the rate of 0.5. Dropping hidden units at higher layers forces the network to learn more compact and abstract representations and reduce overfitting. Finally, a multi-output classification is obtained from two separated softmax logistic regressions for classifying skill and training tasks.

### III. EXPERIMENTAL EVALUATION

#### A. Dataset

We test the proposed SATR-DL on the public-available minimally invasive surgical dataset, JHU-ISI Gesture and Skill Assessment Working Set (JIGSAWS). Details about data collection and variables are described in [14]. The kinematic motion is captured as multi-channel time-series data from daVinci end-effectors with 30 Hz sampling frequency. Four novice trainees (who practice on the dVSS < 10 hours), two intermediate trainees (10 – 100 hours practice) and two expert surgeons (> 100 hours practice) performed five repetitions each of three standard surgical training tasks, suture, needle-passing, and knot-tying.

#### B. Pre-processing

Raw motion sequences are first normalized to a zero mean with unit variance for each individual sensory channel. The original sequences are further processed with a sliding window of size 120 (4-second record) with a step size of 30, yielding a compatible format for the network input regardless of varied recording durations, since the time sequence may vary for each trial. This approach also enables us to obtain a large set of examples applicable for deep learning to avoid substantial overfitting.

#### C. Training & Performance Validation

In this work, all parameters of the network layers are initialized using the Xavier initialization [15]. We train the SATR-DL by minimizing the global cross-entropy loss function using an adaptive learning method. Network parameters in processing units are jointly optimized using mini-batch gradient descent for training efficiency with the Adam update rule [16]. Using this configuration, a total of 80 epochs with 600 mini-batches is run for training. The initial learning rate, \( \epsilon \), is set as 0.005, and the exponential decay rates of the first and second moment estimates are 0.9 and 0.999, respectively. The learning rate is reduced by a factor of 5 once the overall validation loss has stopped improving every three epochs. To obtain a robust learning model, the above hyper-parameters
are fine-tuned via evaluation on validation set, which is split from the training data with the 80/20 partition for training and validation. The best model is chosen from the one that achieves the highest accuracy in validation set.

To validate our proposed deep architecture, we adopt the Leave-One-Supertrial-Out cross-validation scheme (LOSO), which is widely used in current skill assessment studies [14].

IV. RESULTS AND DISCUSSION

We evaluate the classification performance regarding the precision, recall, and f1-score for each output class, and the overall accuracy. These performance metrics are reported as averages of classification across all five-fold LOSO cross-validation evaluated on each testing set.

Figure 3 shows the normalized confusion matrices of SATR-DL predictions for each output class. Table I gives a summary of model performance in the skill and task recognition. This model correctly assesses the trainee expertise with an overall accuracy of 0.920, given a 4-second motion sequence input. Note that a higher accuracy of 0.960 in the recognition of training tasks is achieved compared to surgical skill levels. This result might potentially benefit from the learned information of temporal dynamics, since different tasks are associated with varied motion patterns in the temporal dimension. Table I also compares the aggregated results of classification at the level of trial compared to the interval-level assessment. This result provides evidence that the SATR-DL algorithm can yield better accuracy using ensemble of interval-level classification for each trial.

Furthermore, we compare the overall performance of SATR-DL model with that of state-of-the-art methods in both surgical skill assessment and training recognition, as shown in Table II. All benchmarks are conducted under LOSO cross-validation scheme based on JIGSAWS kinematics data. Using a 4-second data window input, our model outperforms conventional feature-based methods including kNN, LR, and SVM, with at least 6.85% improvements in trainee skill assessment, except for the sparse HMM (S-HMM). For task recognition, SATR-DL provides at least 1.15% accuracy improvements compared with existing methods of HMM, DTW-kNN. Also, for classification at the level of trial, SATR-DL achieves the best performance compared to all other methods, with its highest accuracy of 0.960 in skill assessment and 1.000 in task recognition, respectively.

V. CONCLUSION

In this work, we propose a novel analytical framework with deep feature learning, SATR-DL, to investigate multichannel motion kinematic profiles for an automatic surgical skill assessment and task recognition. The benefits of our proposed SATR-DL are: 1) highly-efficient processing of raw surgery motion via end-to-end learning given a limited data influx, and 2) improved performance of assessment in recognizing trainee skills and surgical activities. Combining a CNN with GRU component, we demonstrate that the SATR-DL architecture can jointly exploit the intrinsic information spatially and sequentially from high-dimensional surgical motion data. In addition to interval-level assessment, we also show that the classification at the level of each trial can exceed published results, derived from conventional statistics and machine learning methods, with an improvement of at least 6.85% and 1.15% in skill analysis and task recognition, respectively. These deep architectures and high-level motion analysis techniques could have the potential to largely improve trainee assessment for robotic minimally invasive surgery.
TABLE I: Summary table of SATR-DL classification performance employed for skill assessment and task recognition at interval-level and trial-level. Performance results on testing sets under LOSO validation scheme are reported in terms of precision, recall, f1-score for each class, and overall accuracy.

| Surgical Skill | Training Task | Interval-level Classification | Overall Accuracy | Trial-level Classification | Overall Accuracy |
|----------------|---------------|-------------------------------|-----------------|---------------------------|-----------------|
|                |               | precision | recall | f1-score | accuracy | precision | recall | f1-score | accuracy |
| Novice        | Suturing      | 0.96      | 0.96   | 0.95     | 0.920    | 0.95      | 0.98   | 0.97     | 0.966    |
| Intermediate  | Needle-passing| 0.88      | 0.77   | 0.82     | 0.900    | 1.00      | 0.90   | 0.95     | 0.98     |
| Expert        | Knot-tying    | 0.90      | 0.95   | 0.93     | 0.970    | 1.00      | 1.00   | 1.00     | 1.000    |

TABLE II: Performance comparison of our proposed SATR-DL with state-of-the-art results under LOSO validation in terms of overall accuracy. The best classification results are highlighted in bold.

| Author, Year | Method | Skill Assessment | Task Recognition |
|--------------|--------|-----------------|-----------------|
| Lingling et al., 2012 [5] | S-HMM | 0.960 | – |
| Fard et al., 2017 [6] | kNN | 0.859 | – |
| | LR | 0.861 | – |
| | SVM | 0.754 | – |
| | HMM | – | 0.924 |
| | DTW-kNN | – | 0.955 |
| Current study | SATR-DL | 0.920 | 0.966 |
| | CNN-GRU | 0.960 | 1.000 |

Fig. 3: Confusion matrices of SATR-DL results in five-fold LOSO cross-validation. (A) trial-level classification, (B) interval-level classification with 4-second kinematics input.

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