A Method for Segmenting the Process of Needle Insertion during Simulated Cannulation using Sensor Data

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***Abstract*— Cannulation is a routine yet challenging medical procedure resulting in a direct impact on patient outcomes. While current training programs provide guidelines to learn this complex procedure, the lack of objective and quantitative feedback impedes learning this skill more effectively. In this paper, we present a simulator for performing hemodialysis cannulation that captures the process using multiple sensing modalities that provide a multi-faceted assessment of cannulation. Further, we describe an algorithm towards segmenting the cannulation process using specific events in the sensor data for detailed analysis. Results from three participants with varying levels of clinical cannulation expertise are presented along with a metric that successfully differentiates the three participants. This work could lead to sensor-based cannulation skill assessment and training in the future potentially resulting in improved patient outcomes.**

I. INTRODUCTION

Cannulation (e.g., intravenous cannulation) is one of the most commonly practiced medical procedures with an direct impact on clinical outcomes. Patients on hemodialysis require cannulation to access their vascular access (an arteriovenous fistula (AVF) or graft (AVG)) for dialysis about three times a week. The cannulation task not only consists of inserting the needles but also appropriate palpation for locating the fistula. Recent research has documented that the quality of cannulation performed by a clinician can be a factor in patients' morbidity and mortality rates [1], [2]. In addition, the lack of requisite skill has contributed to a high rate of miscannulation [3], [4]. To improve and ensure that clinicians are skilled in cannulation, better methods of training and assessment are needed.

One significant limitation in current literature is a detailed understanding of the technical process of skilled hemodialysis cannulation. This requires a multifaceted understanding of various aspects such as the force during needle insertion as well as the 3D trajectory of the needle during insertion. Several groups have developed systems that assess certain clinical procedures using multiple sensor modalities. For instance, Lasso and colleagues combined vision and tracking data streams for image-guided medical intervention training [5]. Along the same vein, both laparoscopic and suturing skills have been measured on simulators that were equipped with sensor systems that yielded multiple objective metrics including gripping force and tool path length, which were postulated to improve training [6], [7]. While it is advantageous to use multiple sensors, it is critical to relate the data to their procedural and spatial context. In other words, for meaningful skill analysis "clips" of sensor data must be related to their specific physical context. An example of this is work by Lin and Hoover who explored the detection of bite counts during food consumption using both finger and wrist motion data [8]. Similarly, Fukuda and colleagues successfully labeled laparoscopic suturing motions, such as probing, pulling-out and dragging, based on force data [9]. Our previous research in assessing suturing skills also involves labeling movements from multiple data streams [10].

This study presents an improved cannulation skill training simulator to better understand the complex process of hemodialysis cannulation by identifying sub-tasks of the cannulation process. Motivated by our promising previous study [11] in quantifying cannulation skills, we included two additional sensing modalities (force and infrared sensing) to further capture cannulation skills. For data analysis from the multiple sensor systems which are integrated within our simulator, an algorithm that segments the cannulation process using specific events is presented. The proposed device and algorithm, in our opinion, lays the foundation for systematic analysis with bigger data sets via batch processing, which could ultimately result in improved cannulation skills training.

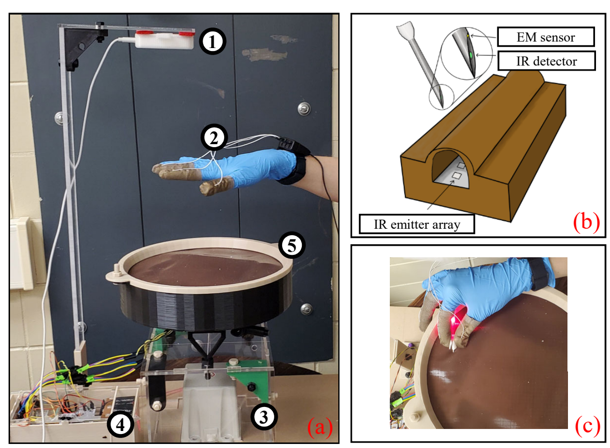

Fig. 1. (a) The Cannulation Simulator: 1. Leap Motion 2. FingerTPS 3. trakSTAR 4. Control Box 5. Simulator Bed; (b) IR Emitter/Detector Pair within the fistula model; (c) Flashback Effect with LED.

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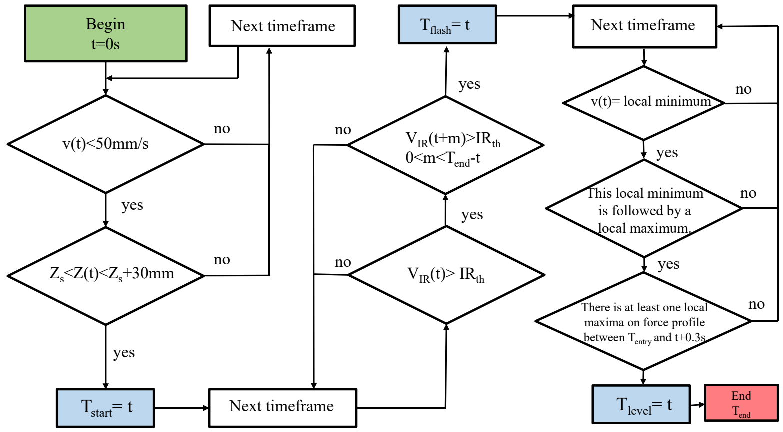

Fig. 2. Cannulation Procedure Segmentation Algorithm as a Flowchart

II. METHODS

In this section, we describe the experimental setup, filtering process of sensor data and the cannulation process segmentation algorithm.

A. Experimental Setup

The cannulation simulator (seen in Fig. 1) consists of four sets of sensors: Leap Motion for tracking the hand (Ultraleap), FingerTPS for measuring forces on the needle (Pressure Profile Systems), trakSTAR for measuring needle motion (Northern Digital Inc.), and infrared (IR) emitters/detectors for detecting whether the needle is inside the fistula. The Leap Motion controller used for tracking hand movement is fixed to the top of the frame. The participant's hand movement while palpating to locate the AVF model to be cannulated could, therefore, be observed and recorded at 100 Hz. The FingerTPS system includes three finger sleeves that cover each participant's thumb, index finger, and middle finger, as these fingers are typically used to palpate and hold needles. Force data is recorded at 40 Hz via a Bluetooth connection to the host PC. With initial calibration, finger force is recorded in newtons; however, due to individual differences among participants, force of each finger was normalized to the [0-1] (unitless) range for analysis. An electromagnetic (EM) field generator from the trakSTAR system is placed underneath the simulator. The corresponding EM sensor is embedded inside the needle, close to the beveled tip. During cannulation, the precise location of the needle is saved at 100 Hz, allowing the capture of subtle movements that may be useful for evaluating skill. Finally, an IR detector is fixed close to the tip inside the needle (shown in Fig. 1(b)). IR LEDs are located along the bottom of each AVF module such that when the needle is inserted correctly into the module, the detector picks up the emitted signal and lights a red LED in the cannula to simulate blood flashback. The IR detector's voltage is recorded at 100 Hz through a DAQ module (USB-6001, National Instruments). This current design, integrating IR emitters and a detector, allows the simulator to be liquid-free while allowing for accurate flashback simulation. To avoid confusion between the IR signal inside the fistula and ambient IR, the IR emitters are excited at a specific frequency (25 Hz square wave) which allows for the isolation of the desired signal during analysis.

B. Signal Filtering and Temporal Synchronization

Among our sensors, the Leap Motion controller and FingerTPS both provide pre-filtered and calibrated data and thus do not require additional filtering. Data from the trakSTAR system, however, must be filtered for noise which is primarily caused by electromagnetic interference from other electronic components and metals (except for medical grade stainless steel). The minor noise measured using our simulator is largely due to the motor and the IR emitter array in each AVF module and can be filtered out using a low-pass filter with a cutoff frequency of 20 Hz. This frequency was chosen since, according to studies [12], [13], human hand motion rarely exceeds 20 Hz. The IR detector data must be filtered with a bandpass filter around 25 Hz to isolate the frequency at which the emitters blink to recognize when the needle is inserted into the AVF module.

Due to the nature of multi-modal sensing, temporal calibration is essential to ensure reliable data. The cross-correlation method was applied to determine the lag between two streams of signals by finding the maximum peak of the sliding dot product [14], [15]. The four sensors were matched by three pairs: FingerTPS and Leap Motion, Leap Motion and trakSTAR, trakSTAR and IR emitter/detector. Throughout the temporal calibration process in this study, only the FingerTPS was found to experience an average lag of 219 ms as expected considering its wireless Bluetooth connection. Because other sensors were all set at the sampling rate of 100 Hz, there was no other lag evidenced. Consequently, this lag was compensated for in the algorithm that will be introduced later in this paper.

C. Recognition of Sub-tasks during Cannulation

Some key events are critical for labeling sub-tasks during cannulation: the starting point of inserting the needle, the time when flashback is witnessed, and the moment of leveling out the needle. In this work, we focus on a method to

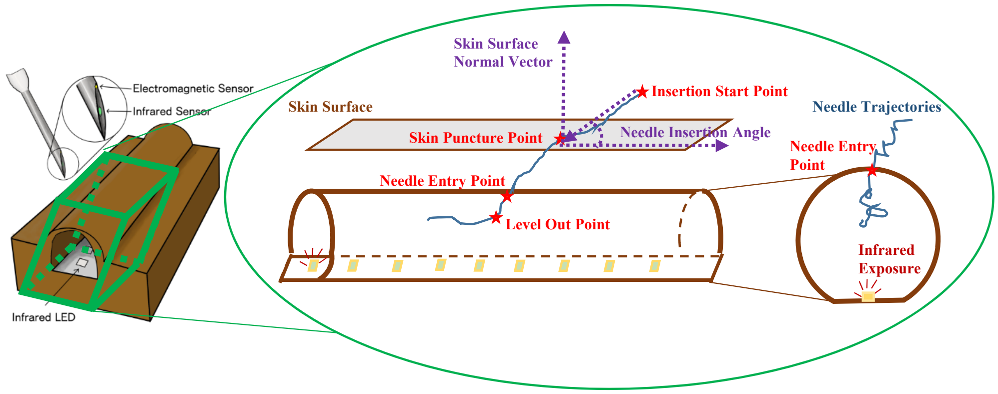

Fig. 3. An illustration of the process of cannulation used to define key events and sub-tasks

segment the various data streams into sub-tasks based on the following events:

- The insertion starting point (T_{start}): This moment can be described as the short pause right before inserting the needle into the skin surface. Since the short pause is used by participants to ensure the cannulation site is accurate, it not only marks the beginning of needle insertion, but also provides information on the participants' success in locating the optimal cannulation site from the palpation exam. In Fig. 2, $Z(t)$ represents the location of the needle in the Z-axis at time t in reference to the trakSTAR EM field generator coordinates and Z_s stands for the height (Z value) of the skin surface.
- The needle flash point (T_{flash}): This moment is defined as the time that participants first receive steady flashback. In Fig. 2, V_{IR} stands for the filtered voltage reading from the IR detector and IR_{th} is the voltage threshold for identifying whether the LED should be turned on.
- The leveling out point (T_{level}): This moment is described as when participants start to adjust and push the needle into a secured position after seeing flashback. Such movement can be found by locating local maxima and minima on the needle velocity profile $v(t)$. Because participants need to advance the needle at an angle that is different from the one used for needle entry, it is expected that there is a local maximum on the finger force profile near this time point as well.

D. Experimental Design

In this study, data from three participants who represented three distinct skill levels were analyzed. Skill levels were evaluated by expert peers using a rating sheet. Each participant was presented with identical written instructions on how to complete the experiment which included cannulating fistulas 16 times on the simulator. However, each time a unique condition (a combination of AVF location, AVF shape, vibratory sensation, and skin thickness) was presented. Ethics approval for this study was provided by the Institutional Review Boards (IRB) of Clemson University and Prisma Health (Greenville, SC).

III. RESULTS AND DISCUSSION

A. Identification of Sub-Tasks

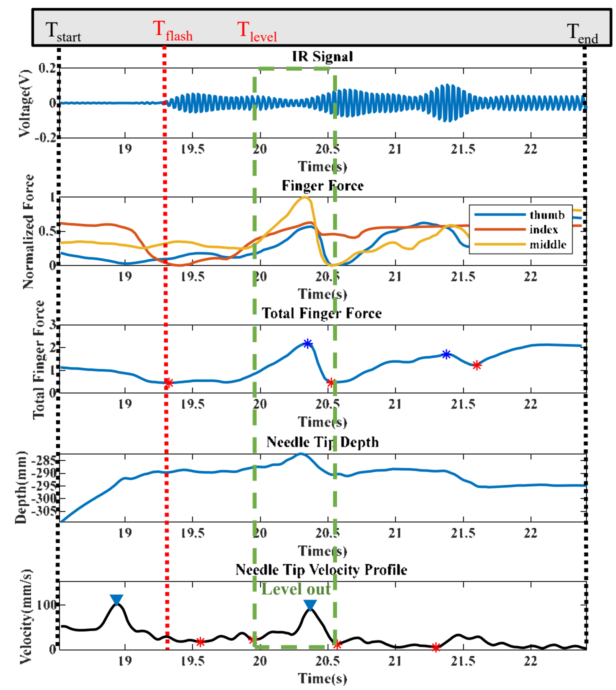

Fig. 4. Segmented cannulation procedure of one trial from an expert cannulator *(Note: All force values are normalized and, therefore, unitless.)*

Fig. 4 shows the data recorded from a peer-recognized expert participant. According to the algorithm, the first flashback occurs at 19.34 s. There is one major peak on the velocity profile representing a swift needle insertion around 19 s, right before the needle flash point. After flashback, another major peak is seen on the velocity profile that is accompanied by an almost simultaneous peak on the force profile. This was produced by the subconscious movement of squeezing the wings of the needle to level out the needle angle and to push it into a secured position. The start of the leveling out movement is identified as the adjacent local minimum (19.95 s) before the major peak on the velocity

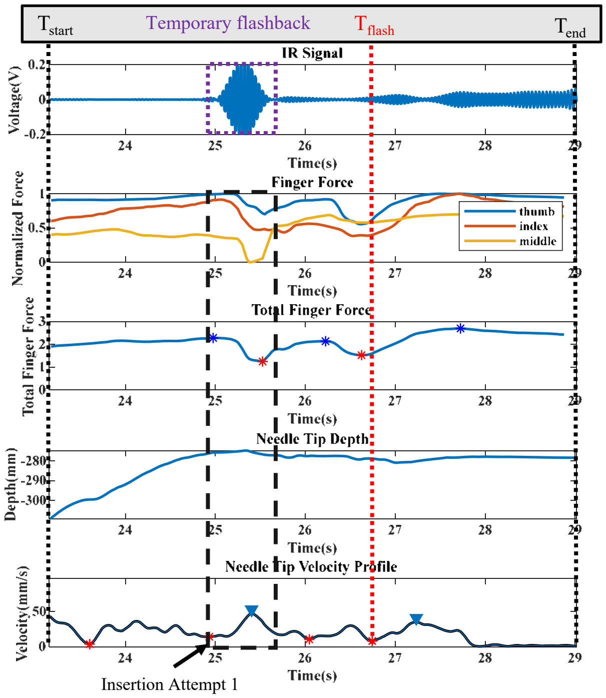

Fig. 5. Segmented cannulation procedure of one trial from an intermediate cannulator *(Note: All force values are normalized and, therefore, unitless.)*

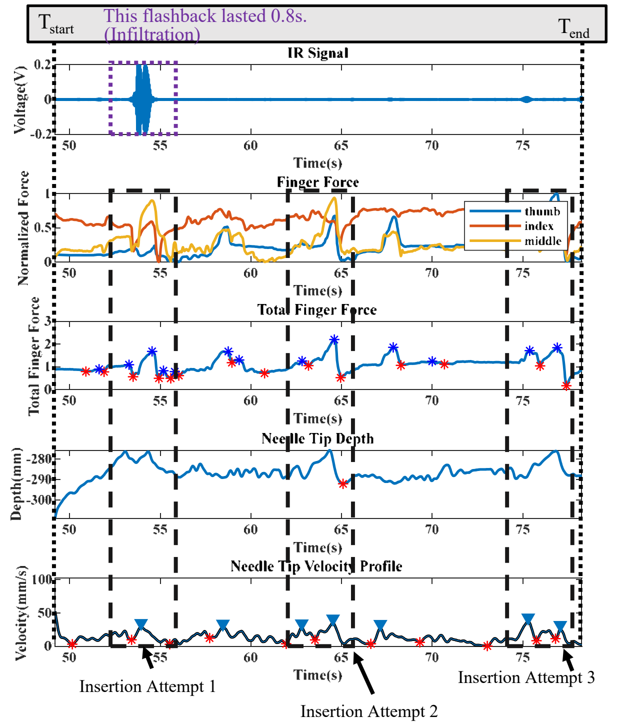

Fig. 6. Segmented cannulation procedure of one trial from a novice cannulator *(Note: All force values are normalized and, therefore, unitless.)*

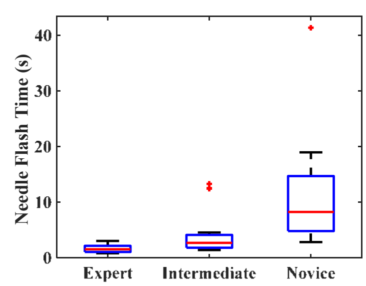

Fig. 7. Comparison of Needle Flash Time (T_{flash}-T_{start})

profile. This clip of data describes a clean, swift, and efficient cannulation trial which is preferred during training. Within the 16 trials of this expert participant, there are 5 trials in which no obvious leveling out movement can be detected. Also, the number of major peaks on the velocity profiles are calculated based on the specific sub-task time segment of the cannulation procedure. For the expert participant, the number of extra movements before the needle flash point and after the leveling out point is very limited. Among 16 trials, only 1 trial scored three major velocity peaks before needle flash point.

Fig. 5 demonstrates an example of a trial performed by a participant with intermediate cannulation skill. At time 26.84 s the needle flash point is marked by the first sight of steady flashback. Before this point, there is one major local maximum (Insertion Attempt 1) recognized on the velocity profile and only temporary flashback is observed. Although there is one local maximum of velocity after the needle flash point, the pattern is considered to fit the insertion motion instead of needle leveling out. After checking with the video evidence, we are confident to say there is no clear leveling out movement in this trial. For this specific participant, the movement of leveling out is constantly skipped. Out of 16 trials, 10 cannot be identified with clear leveling out movements. Another discovery is that the number of local maxima of the velocity profile before the needle flash point is more sporadic (median=2).

Fig. 6 shows an example of a cannulation trial by a novice participant. There is no steady and constant flashback according to the IR voltage level, although there is a brief period in which the voltage of the IR detector indicates that the needle was in the AVF model. A brief flashback which goes away immediately after fits the pattern of needle infiltration. During this trial, this participant made 3 attempts and each attempt can be identified by combining needle tip depth, total finger force, and velocity profiles. Future effort is needed to systematically quantify these attempts. Compared to the examples of the other two participants, this was far from a successful cannulation. Among the total of 16 trials, there are 7 trials that this participant failed to obtain steady flashback, while the other two participants successfully obtained steady flashback for all 16 trials.

B. Comparison of Participants' Performance

Using the algorithm proposed here, we divided the cannulation procedure into multiple sub-tasks. From this, we extracted the needle flash time as a metric to compare performance. Ideal cannulation is assumed to be swift and time-efficient as it can be verified by needle flash time. Fig. 7 presents the time it takes the participant from the start to the needle flash point. Using the Kolmogorov-Smirnov test, there is not enough evidence to prove this set of data is normally distributed. Therefore, the non-parametric t-test (Wilcoxon rank-sum test) was used in this case to determine if the data in each sample group have equal medians. Between expert and intermediate participants, their medians are different ($T_{expert}=1.53$ *vs* $T_{intermediate}=2.68$*:* $p=0.0019$); between intermediate and novice participants, their medians are different as well ($T_{intermediate}=2.68$ *vs* $T_{novice}=8.24$*:* $p=0.01$). The level of significance is set at 0.05.

From the results described above, the sub-task of "level out" is most often skipped among the trials performed by the intermediate and novice participants. For the expert participant, out of 16 trials, there are 5 trials in which our algorithm and video evidence cannot detect any obvious level out movement. For the intermediate participant, out of 16 trials, there are 10 trials in which a level out movement cannot be detected; as for the novice participant, only 1 trial contains a level out movement. Another discovery is that for the expert participant, the number of peaks from the velocity profile before the needle flash point is very consistent (median=1). Meanwhile, the results from the other two participants vary greatly, especially for novice participant, whose median of the number of peaks from the velocity profile is 5.5.

IV. CONCLUSION

In this study, we captured the cannulation process at varying skill levels via sensor data. There are four main subtasks or metrics that set the expert participant apart from the other subjects in the study. First, the expert user moved smoothly through the task, shown by typically peaking in velocity once before flashback while the less experienced participants had a significantly higher number of peaks. Second, the participant's movement was swift, as the needle flash time after the start was consistently small, while less experience is shown by long and unpredictable times. Third, the expert participant did not fail to get flashback as the others did. Finally, the leveling out movement was observed most often with the expert participant while the intermediately experienced participant leveled out about half as often, and the novice leveled out only once.

Dividing the task into sub-tasks allows for focused training at key steps of the cannulation process. It can expose areas of weakness in participants' technique or skill and provide objective metrics for assessment and find areas of improvement. As machine learning and neural network algorithms start to show great promise in clinical training and assessment [16], [17], the algorithm proposed here can be improved to analyze large groups of data to sort performance based on skill levels. Assessing data in this way could provide insight into improvements that clinicians could make for more efficient and safe cannulation. In the future, we are willing to include an interface that provides immediate feedback to the participants during cannulation while providing comprehensive metrics.

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