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1. Activities, Accomplishment and Findings

1.1. Data annotation

The Mitsuishi Laboratory, Department of Mechanical Engineering, School of Engineering, provided the following synchronized data:

- 27 videos of robotic artificial blood vessel micro suturing task performed by 6 participants,
- The corresponding kinematic data (i.e. position and orientation of the surgical instrument as well as the grasping angle and voltage) for both robotic arms.

For the procedural analysis purpose, the first step consisted in describing the task. Then, we defined a vocabulary and we manually annotated videos thanks to a dedicated software (*Surgery Workflow Toolbox* [Annotate]) to generate procedural sequences. Procedural sequences were created for three different granularity levels [1]:

- Phases: the main periods of the intervention. A phase is composed of one or more steps.
- Steps: a step is a sequence of activities used to achieve a surgical objective.
- Activities: An activity is a physical action performed by the surgeon.

Currently, 17 sequences have been manually generated. Among these 17 sequences:

- 4 was performed by surgical expert 1,
- 3 by surgical expert 2,
- 4 by engineering student 1,
- 6 by engineering student 2.

1.2. Task 1: Distinction of invariants and variants in practice between surgeons with different expertise

1.2.1. Technical aspects

For this part, available data contains trajectories information only with no force measurements. Consequently, only trajectory analysis was possible. We analyzed trajectory sequences through three different approaches:

- Two on pattern discovery methods previously developed in [2] and [3],
- One relying on a kinematic metric-based approach [4]

In both pattern discovery methods, trajectories have been encoded using the SAX algorithm [5]. The first method [2] relies on the encoded trajectories to extract two bag of words corpuses (one by level of expertise) and used the term frequency and the inverse document frequency (*tf*idf*) to classify. We were able to discriminate the level of expertise with an accuracy of 83%.

The second method [3] consists in studying transition between values of the encoded trajectories and searched patterns (i.e. all successive transitions which were present at least a number of times in all encoded trajectories). These patterns allow detecting some variants and invariants according to participants and their expertise level (surgical expert or engineering student). With the optimal parameters, we identified:

- 69 patterns,
- 12 are present in both students,
- 2 are present in both experts,

- 3 are only present in student 1,
- 8 are only present in student 2,
- 2 are only present in expert 1,
- 1 is only present in expert 2.

The last method consists in analyzing the data directly at the numerical level. The objective of this method is to compute similarity between time-series data (i.e. one trial performed by a surgeon generates one time-serie) using the Dynamic Time Warping (DTW) distance [4]. Then, computing all distances between time-series filled a global distance matrix that is used next as input for the Ascendant Hierarchical Clustering (AHC) unsupervised algorithm. At the end, we obtained groups of similar trajectories with respect to the participant expertise (i.e. expert or student).

1.2.2. Procedural aspects

We used an alignment approach called Non-Linear Temporal Scaling (NLTS) [6] onto the procedural sequences. NLTS is an improvement of the DTW distance that allows, among other things, to do local comparison between multiple sequences.

We highlighted the following points:

- Micro suturing task presents no or little variability between sequences at the phase and step granularity levels (Figure 1);
- At the activity level, the task presents a high variability between sequences (Figure 2).

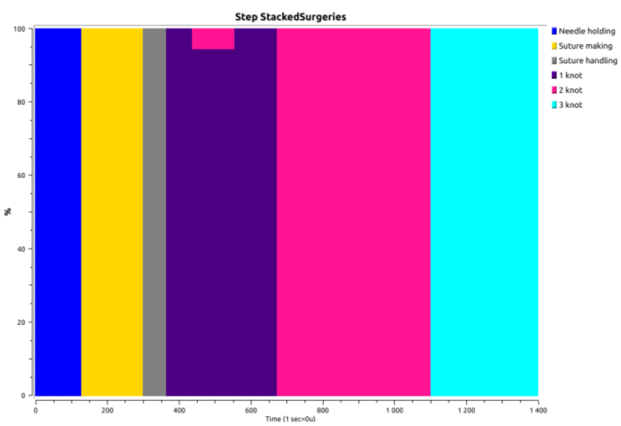

Figure 1: Step sequence representation of the 17 sequences after NLTS alignment. Each color represents a specific step.

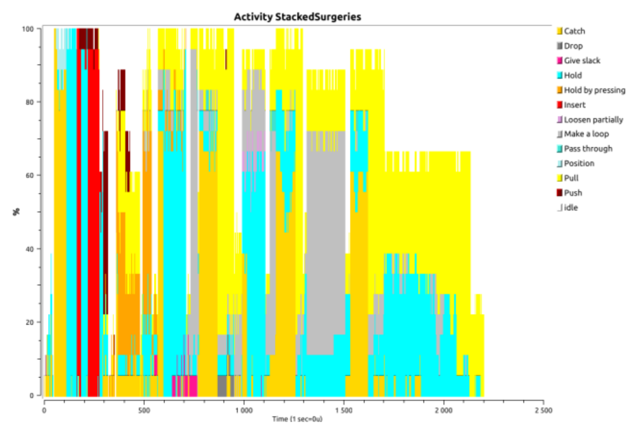

Figure 2: Activity verb sequence representation of the 17 sequences after NLTS alignment. Each color represents a specific activity verb.

As for the unsupervised kinematic data analysis, we used the pattern mining approach [3] to identify patterns in procedural sequences. In this case, a pattern is a sub-sequence of activities. With the optimal parameters, we identified:

- 76 patterns,
- 13 are present in both students,
- 6 are present in both experts,
- 12 are only present in student 1,
- 22 are only present in student 2,
- 3 are only present in expert 1.

Then we applied the AHC algorithm to the appearance frequency of each pattern. We obtained the following clustering (Figure 3). It highlights that expertise of the surgeon is integrated as a dedicated "signature" into both kinematic data and surgical activity patterns.

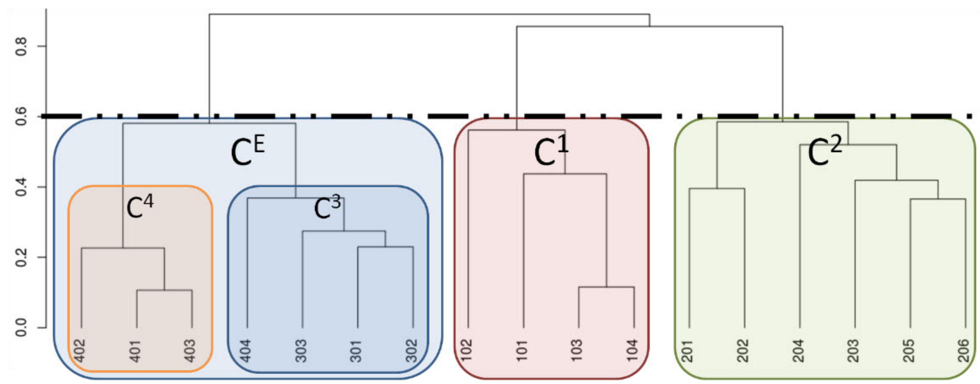

Figure 3: Pattern appearance frequency clustering. Each color highlights a cluster of trials from one participant. Groups are directly linked with the expertise (i.e. Expert 'C3', 'C4' and Student 'C1', 'C2').

1.3. Task 2: Assessment and understanding of variance/invariance

1.3.1. Technical aspects

Even if we have been able to detect patterns in kinematic data, their meaning is still not understandable yet. Figure 4 represents trajectories found as a pattern 7 times in 4 experts' encoded sequences (only 3 trajectories represented). Each trajectory is very different from the others. The lack of pattern relevance could be explained by the large range of motions required during the task as well as by the fact that the chosen encoding method (SAX) used predetermined thresholds to encode data. Our next step will be to improve this methodological part by applying other encoding methods

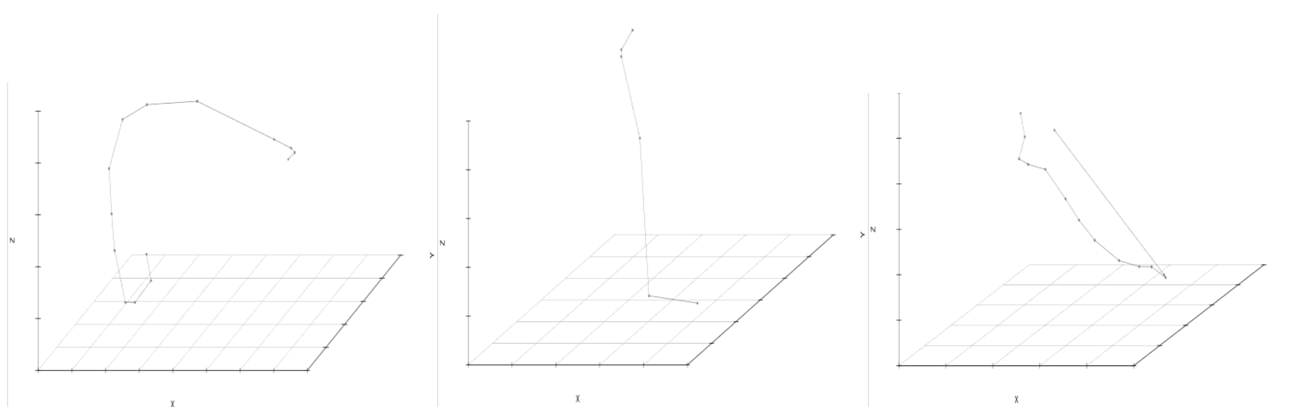

Figure 4: Three trajectories representations of a pattern present 7 times in 4 experts' encoded sequences.

1.3.2. Procedural aspects

The study of procedural patterns allowed us to identify different leads in order to provide relevant assistance to the surgeon. For example, we have identified:

- A signature that illustrates the full knot tying process without unnecessary activities,
- A signature that reflects a mistake independent of the expertise level.

With procedural patterns, we are able to determine what is the participant expertise level who made a new trial and its id also. To determine these trial's characteristics, we conducted a leave one out cross-validation study. We identified all patterns present in all sequences except one. For each of them, we determined whether it was specific to one of these characteristics. For the remaining sequence, we checked presence of these patterns. According to their specificities, we determine the remaining trial's characteristics. We are able to predict the expertise level in all case without any mistake (100% prediction and 100% accuracy). For the participant id, we predicted at 82% with an accuracy of 64%.

2. Outreach, Events and Other Activities

None.

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