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Development of an intelligent surgical training system for Thoracentesis

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ABSTRACT

Surgical training improves patient care, helps to reduce surgical risks, increases surgeon's confidence, and thus enhances overall patient safety. Current surgical training systems are more focused on developing technical skills, e.g. dexterity, of the surgeons while lacking the aspects of context-awareness and intra-operative real-time guidance. Context-aware intelligent training systems interpret the current surgical situation and help surgeons to train on surgical tasks. As a prototypical scenario, we chose Thoracentesis procedure in this work. We designed the context-aware software framework using the surgical process model encompassing ontology and production rules, based on the procedure descriptions obtained through textbooks and interviews, and ontology-based and marker-based object recognition, where the system tracked and recognised surgical instruments and materials in surgeon's hands and recognised surgical instruments on the surgical stand. The ontology was validated using annotated surgical videos, where the system identified "Anaesthesia" and "Aspiration" phase with 100% relative frequency and "Penetration" phase with 65% relative frequency. The system tracked surgical swab and 50 mL syringe with approximately 88.23% and 100% accuracy in surgeon's hands and recognised surgical instruments with approximately 90% accuracy on the surgical stand. Surgical workflow training with the proposed system showed equivalent results as the traditional mentor-based training regime, thus this work is a step forward a new tool for context awareness and decision-making during surgical training.

1. Introduction

Surgery is a highly complex process that requires excellent technical skills [1] e.g. dexterity, procedural knowledge, non-technical skills, e.g. cognitive skills (context awareness, decision-making, and planning) [2,3], and clinical skills [4] e.g. assessment, diagnosis to achieve better patient outcomes and to improve the quality of performance in the operating theatre. Recently, following the emergence of new technologies, e.g. robot-assisted surgeries, the focus on surgical care is moving also towards the quality rather than only on the quantity of the procedure performed. The quality was also further enhanced with the recent advancements in surgical training regimes e.g. by employing surgical simulators [5,6] in advanced surgeries, e.g. thoracic surgeries. In a particular study, researchers [7] have shown that technical errors account for only 4.3% of errors during surgery, while most errors are non-technical errors and pertain the clinical decision-making process. Although context awareness is an important cognitive skill of the surgery and part of the decision making, most of the current surgical training environments are focused on improving only surgeons' technical skills. The surgeon's capacity to make the intra-operative situational judgements are influenced by surgeon's technical capabilities, patient's conditions, and the competence of the assisting trainee [8]. As traditional training methods are designed under the mentorship of different expert surgeons, the competence of expert surgeons is prime and training could be highly variable. Mental models of the surgeon's experiences stored in the memories of interventions and clinical situations influence the judgements related to context awareness [8]. Novice surgeons who learn to perform high-risk interventions extensively use rule-based decision-making. With long-term experience and training, these rules can be retrieved from the memory with little or no efforts [8]. Also, the growing presence of intra-operative sensors, e.g. endoscopic cameras, and representational information, e.g. on monitors, during the procedures make the surgical training more difficult without the explicit understanding of the procedure along with the contextual awareness. In envisaged operation theatres [9], the efficacy of the operation will be achieved by addressing the workflow issues, where study participants also highlighted context

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awareness as an important functional requirement. The research also suggested that there is a lack of information on resources necessary to support surgical tasks and to efficiently plan the surgical process, which increases the surgical workflow variability and could be structured by grounding surgical process information in the ontology.

As a prototypical scenario, we chose Thoracentesis procedure. Pleural effusion is a life-threatening condition, often associated with other diseases, in which there is a collection of pathogenic or non-pathogenic fluids between the lung tissue and pleural space. Common symptoms of pleural effusion are pleuritic chest pain, coughing, and dyspnoea [10]. An invasive procedure, Thoracentesis, is performed for the removal of fluid from the pleural cavity. A needle is inserted into the chest cavity and the fluid withdrawn using a syringe [10]. Procedure-related complications occur with at most 33% of people and are a major problem, and can range from pain, dry cough, no fluid return, or subcutaneous collection. Many life-threatening complications also arise due to surgical mishandling such as pneumothorax, pulmonary oedema, unintentional puncture of spleen or liver and sheared off catheter in the pleural space and in some exceptional conditions such as winging of the scapula [11]. Indeed, although Thoracentesis is a very simple procedure, procedure-related complications are higher than expected. A recent survey highlights gaps of knowledge and skills in conducting diagnostic and therapeutic Thoracentesis and shows significant training gaps as well [12]. Due to lack of experience (65% cases) and lack of expert supervision and guidance (49% cases), junior doctors were referring their patients to radiology departments for ultrasound guided Thoracentesis in majority of cases (75–100%) [13]. The survey highlights junior doctors' deficiency in knowledge and procedural skills in performing Thoracentesis. Simulation-based training [14] and phantom model-based training [15] on Thoracentesis has enhanced skills of the surgeons; however, the training systems were focused on manual dexterity and lacked the aspects of context-awareness, intra-operative real-time guidance. Thus, there is indeed a need to create an intelligent training system.

We implemented an intelligent training system using knowledge-based system engineering. In this context, an ontology can be applied as a knowledge representation approach for process model that represents key concepts with their properties, relationships, and constraints for Thoracentesis. An ontology provides a rich set of relationships between domain concepts, generally a set of 'part-of' or 'is-a' relations, and allows semantic rules to administer those relationships. In general, ontology holds all pertinent knowledge about the surgical procedure and can be represented in a computer interpretable format to reason over that knowledge to infer information on surgical tasks. Our approach for object recognition consists of the amalgamation of knowledge representation and sensor data to recognise surgical instruments in surgeon's hands for detecting surgical steps and on the scrub nurse surgical stand for further guidance on the required instrument in the next step of the surgical process. Knowledge representation and rule-based machine learning are involved in the object categorization process. Knowledge-based systems [16–18] have been used for object recognition by building a well-defined set of vocabularies for the domain of interest. Unfortunately, most of the algorithmic concepts in 3D computer vision are data-driven and recognition is mostly accomplished by describing the object's geometrical (roughness, curvature, for example) or physical features (colour, texture, for example). Data-driven technologies heavily rely on algorithmic parameters and the object features itself. Moreover, these methods are highly static and few times do not achieve desired results in dynamic settings.

We previously developed [19] an ontology-based context-aware system framework for surgical assistance by combining image processing and semantic technologies to recognise surgical instruments on the surgical stand during Thoracentesis steps. The framework consisted of a Graphical User Interface (GUI), where user queries the surgical step, and then the retrieved step is sent to the ontology component through Robot Operating System (ROS) [20] topics and messages. The ontology component finds an instrument instance corresponding to the surgical step in progress by reasoning on the logical propositions specified in the ontological assertion box [21]. After recognising the instrument instance, a template-matching algorithm was used to recognise the instruments on the surgical stand. The system identified the contexts, e.g. surgical instrument, by a manual query on the surgical task, e.g. the requirement of a 50-ml syringe to withdraw the fluid from the chest cavity.

In this article, we discuss the rule-based intelligent surgical training system, which uses ontology as a knowledge base, production rules as a workflow model, and computer vision techniques for object detection. The rule-based inference mechanism removed the need of complex queries, manual input from the users, and structured the surgical workflow for automatic workflow execution. We also included the inference mechanism within the ontology to recognise surgical instruments and materials. Surgical workflow was constructed as mutual influences between the surgical tasks. The system does compliance checking between the prescribed workflow and the observed actions. Therefore, the developed system needs the results, e.g. information, on the earlier step and next instrument, from the previous surgical task as an input to execute the workflow sequences. The developed system also offers a low-level understanding, e.g. information on surgical actions, for each surgical step. The developed system provides automatic interpretation of surgical workflow and help trainee surgeons to learn Thoracentesis workflow efficiently, and eventually it may improve the patient care.

2. Materials and methods

2.1. Context-aware software framework for intelligent training system

The framework for intelligent training system comprises three components to automatically derive information on the surgical workflow for surgical training and contextual awareness:

1. *Knowledge module*, where we implemented procedural knowledge on Thoracentesis in the form of an ontology and surgical workflow management through inference rules;
2. *Computer vision module*, where we implemented a) segmentation and tracking algorithms in the "Segmentation node" and "Tracking node" respectively to detect surgical instruments/materials using point cloud data acquired from two imaging sensors; and b) "Markers node" – binary square fiducial markers for surgical instruments/materials recognition.

2.2. Knowledge module

2.2.1. Ontology for Thoracentesis

Ontology for Thoracentesis was built using a top-down approach, where most general concepts of the domain, such as phases (e.g. "Penetration") were first analysed and thereafter specialized concepts, such as actions (e.g. "WithDrawLargeSyringe"), were implemented. The needed information about Thoracentesis was obtained from a journal article [22], several online web resources, which were selected through HONcode search engine [23] for health information authenticity, and asking the opinion of a physician. The latter information was then analysed using the

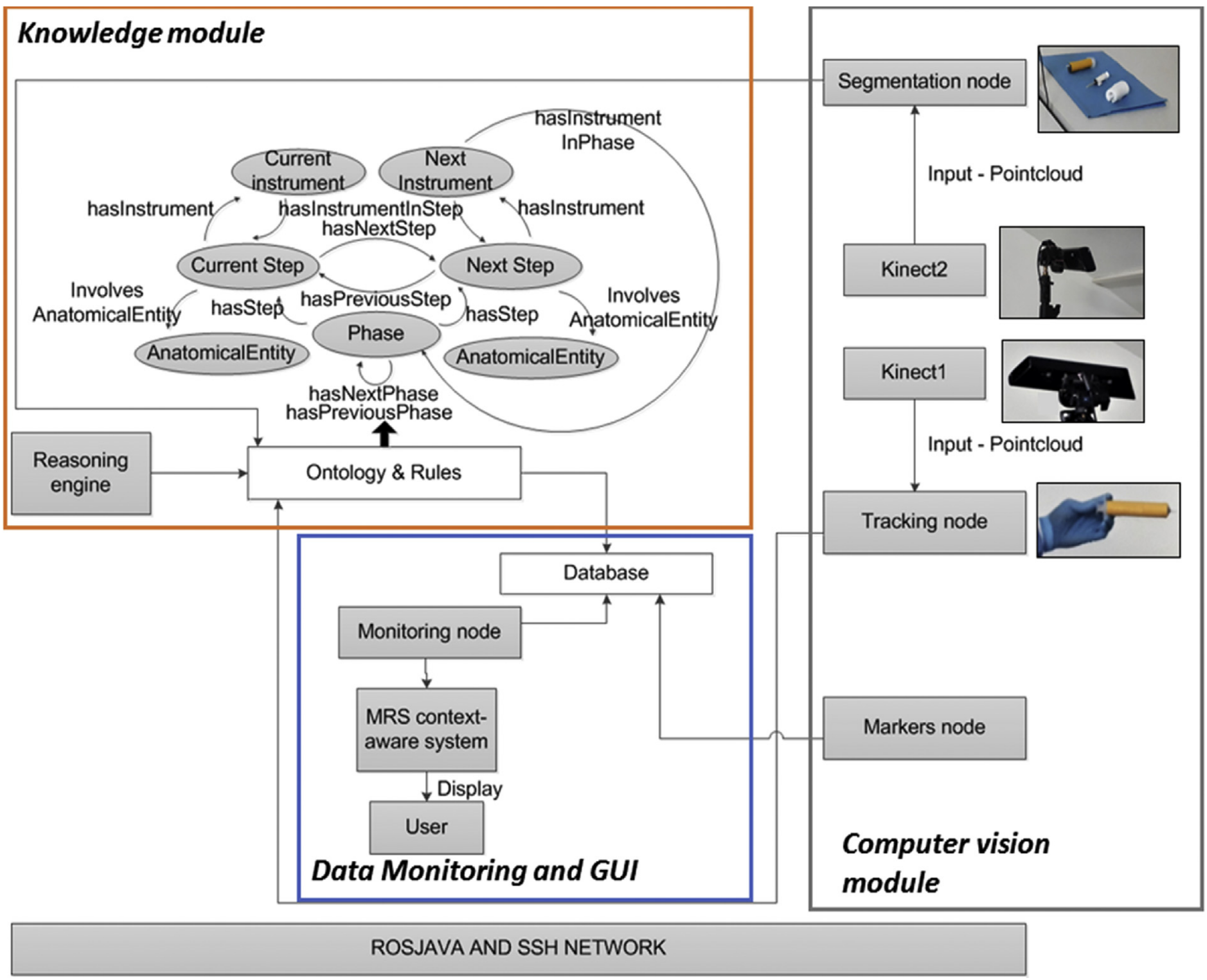

Fig. 1. The framework consists of 1) *knowledge module*, framed in orange colour, consisting of ontology, rule-base and a reasoning engine, e.g. Pellet [21]. Ontology, example surgical process schema and definitions are shown in grey colour ovals, is used to provide the controlled vocabularies that is used to represent the knowledge on Thoracentesis and its activities; and 2) *Computer vision module*, framed in grey colour, consisting of segmentation, marker recognition and tracking nodes. Our framework uses ROSJAVA, ROS topics and messages, and SSH (Secure Shell) network protocol to pass information between the knowledge module and the computer vision module and to facilitate the communication between two modules. 3) *The data monitoring and GUI, "Monitoring node" and "MRS context-aware system"*, framed in blue colour, is used to do constant real-time monitoring of the database, e.g. populated based on the instruments' geometry and changes in the ontology, and to represent relevant information on surgical activities on the GUI. The overall system control is managed by the inference rules, which are used to a) control automatic surgical workflow management b) recognise instruments in surgeon's hands and c) recognise instruments on the surgical stand. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Rule syntax 1: Ontological reasoning with sensor data: "**If** 'instrument-and-instances' representing the real-world object and implicit description of object obtained through the image processing, **then** 'retrieve-instrument-and-its-model' information from the ontology". The rule was used to recognise instruments by geometric features extracted from the sensor and ontological knowledge.

Rule syntax 2: Ontological reasoning for the surgical process model: "**If** surgical step and instances of a recognized instrument is present **then** give information about current, previous, and next step of the procedure from the ontology". The rule was used to recognise the surgical activities.

Rule Syntax 3: Ontological reasoning with explicit information obtained to find implicit information: "**If** instances of a recognized instrument for the next step is present, **then** identify instrument model by segmenting the instrument from the surgical stand". The rule was used to recognise instrument from the real-world to be used in the next predicted surgical activity.

Fig. 2. Basic rules syntaxes that are required to accomplish the instrument recognition-driven automated surgical process model. It is assumed that rules are executed in the sequence of 1–3 for each surgical activity and instances for anatomical locations are grounded explicitly in the ontology for each instrument.

method described in [24] for the ontology development. HONcode allows to choose the reliable and useful medical information on the internet. The procedure was formalised using an approach like [25], where logical sentences were divided into triplets in the format of "Phase (Instrument, Step, Body Structure)", specified for each surgical phase, and surgical actions were linked to instruments and body structures. The developed ontology is based on an upper ontology (Basic Formal Ontology) [26]. Furthermore, we have integrated

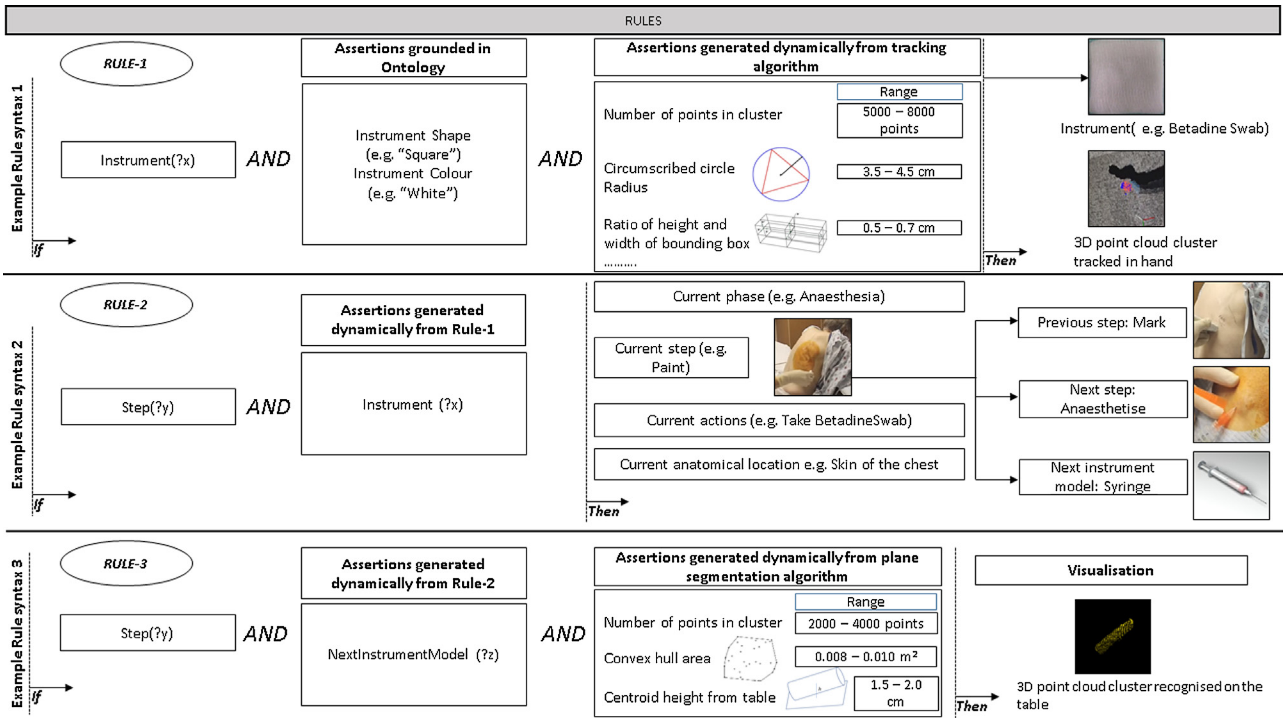

Fig. 3. A rule execution example for "Anaesthesia" phase of Thoracentesis for surgical training by contextual awareness.

relevant parts of Foundational Model of Anatomy (FMA) [27], Information Artifact Ontology (IAO) [28] and W3C time ontology [29]. Theses ontologies are widely used in biomedical informatics and semantic web domain. We also identified several upper-level entities from OntoSPM ontology [30], an emerging common ontology for surgical process modelling, which also uses BFO and FMA for knowledge representation purposes. We extracted upper ontological entities using OntoFox tool [31].

The developed ontology is not only useful for contextual awareness but also to represent the full surgical workflow entities for Thoracentesis procedure. To create the surgical process model, we built the production rules, which map asserted instances and properties of Thoracentesis instruments, e.g. 50 mL syringe and surgical swab, with the asserted data-driven features of instruments in the ontology for instrument's classification. The values of features are dynamically inserted for the instances inside the ontology to recognise relevant surgical phase. The result of situation interpretation, from ontology, is to recognise current surgical phase and recommend the next step and verify the previous step. As a knowledge management tool for ontology, Protégé [32] version 5.0.0 was used.

2.2.2. Production rules and surgical process modelling

We implemented production rules to build the surgical process model. The implemented production rules were in the form of an implication between the antecedent (the statement comprised in "*if*" clause) and the consequent (the statement after "*then*" clause). The rules assume that consequent actions, e.g. information on the step, are only executed if antecedent conditions, e.g. recognition of the instrument, are satisfied. Rules are assumed to match ontology-based surgical knowledge with the data from sensors to infer the knowledge on surgical process model. As a conflict resolution strategy, which helps to choose which competing production rule to fire, rules, which already fired, were not considered for the recognition of phases. For example, "50 mL syringe" is being used two times during "puncturing the chest wall" and during "withdrawal of fluids", however the rule execution is not considered once the rule for puncturing the chest wall through 50 mL syringe is executed. The next inference was achieved through the relationship between steps.

As shown in Fig. 2, we derived the basic rules for modelling surgical workflow of any surgical procedure that requires contextual awareness through ontology and image processing.

Fig. 3 represents example rules for the surgical workflow of the "Anaesthesia" phase of the procedure, where the system recognises the step based on the current instrument in surgeon's hand and suggests the next instrument required for the next step. "*RULE-1*" is used to recognise the instrument, e.g. "BetadineSwab", a material used to sterilise the skin of the chest, in surgeon's hand through a tracking algorithm as explained in section 2.4.1. "*RULE-2*" uses the already obtained information, based on "*RULE-1*", on instrument type to predict the status of the current surgical step and knowledge to accomplish the step e.g. surgical actions. Further to that, the rule recognises predictive information on the previous and next step based on ontological constraints "hasPreviousStep" and "hasNextStep", respectively. The rule is also used to extract the information on the next instrument that is required in the next step. "*RULE-3*" recognises the instrument from the surgical stand that is required in the next step of the surgery, e.g. "Anaesthetise". A total of 12 rules were implemented, comprising instances of facts assertion box. Two rules were implemented to recognise two surgical tools e.g. betadine swab and 50 mL syringe, either in hands or on the surgical stand, and rest of the rules were implemented to build the surgical workflow and recognition of surgical phases. The total number of antecedent conditions were 6 for tools recognition e.g. "hasRatio(?x,?r) ŝwrlb:greaterThan(?r, 0.5) ŝwrlb:lessThan(?r, 0.9)" etc., and 2 for surgical phases e.g. "hasInstrumentInStep(?x, BetadineSwab)" etc. The total number of consequent conditions was 3 for tools e.g. hasModel(?x, LargeSyringe)" etc., and 6 for surgical phases e.g. "hasNextStep(?x, Withdraw)" etc. The conditions were repeated in the consequent part where there were more than one condition representing the similar surgical entity e.g. more than one action in a single step. Although Semantic Web Rule Language (SWRL) [33] was expressive enough for Thoracentesis workflow interpretation, it was not able to handle uncertainty of features obtained after segmenting the tools, explained in Section 2.4.1. Also, as SWRL was not sufficiently expressive to do operations on complex numerical representation e.g. feature vector, we could not be able to add more features for instrument recognition.

We used SWRL [33] and Ontology Web Language – Description Logic (OWL-DL) [34] to do rule-based deductive reasoning within the ontology and to realise the surgical process model. We used Pellet [21] as a reasoning engine for the rules and ontology.

2.3. Data acquisition framework

We used imaging sensors, Microsoft Kinect for Xbox 360 (Microsoft, Redmond, WA, USA), for detecting the surgical tools in the scene. We acquired 3D point clouds, with a maximum acquisition frequency of 30 fps, to extract instruments' geometric features, for recognising surgical instruments in surgeon's hands (Kinect1) and on the surgical stand (Kinect2), as shown in Fig. 1. The data and relevant information were handled and stored using the non-SQL (Structured Query Language) based data storage on the file system, where concurrent access to the data files was established between two modules through SSH communication protocol, ROS, and with the help of Java NIO [35] to detect the changes in workflow entities, such as instruments, after retrieving from the ontology. Python Watchdog [36] library was used to constantly check the file system events to detect changes in the directories comprising the intelligent system database.

2.4. Computer vision module

There are two levels of abstraction for accomplishing surgical instruments recognition in the implemented framework for surgical training:

2.4.1. Image processing level

(1) We used particle filter to detect instruments in surgeon's hands [37], where outliers were removed with the help of statistical outlier removal [38] by analysing k-nearest neighbour distances for each point, and a bounding box around the tracked segment was created using Principal Component Analysis (PCA). Moreover, to optimize the algorithm, we used Kullback-Leibler Distance sampling (KLD-sampling) [39] for adapting the size of the particle filter during the computation of the Kullback-Leibler distance (KL-distance) [39]. We extracted several features, such as (i) number of points in the cloud; (ii) length of the instrument; (iii) ratio of height and width of the instruments; (iv) circumscribed circle between segment's centroid and the points at cloud's maximum and minimum x-values. These features were used to recognise surgical instruments in surgeon's hands.

For recognising surgical instruments on the surgical stand, we used RANSAC algorithm [40,41], which is a widely-used computer vision technique to segment planes by estimating parameters of a mathematical models, e.g. the plane, from a set of data points. We down-sampled the points clouds, e.g. to 0.01 m, and approximated the region of interest, with the help of voxel-grid and pass-through filters to decrease the point density and to remove the outlier points, such as walls [42], respectively. Conversely, we also used RANSAC-based plane segmentation to extract instruments' surface patches on the surgical stand. We extracted surface patch's (i) number of points in the cloud; (ii) instrument's centroid height from the plane, e.g. surgical stand; and (iii) area and volume of the convex hull representing instrument abstract size. We implemented particle filter and RANSAC-based plane segmentation in Point Cloud Library (PCL) [43].

(2) As shown in Fig. 4, we implemented ArUco markers [44] of size "20 mm x 20mm" placed on each of the surgical instruments, where a separate "id" was assigned to each of these markers to successfully recognise the instrument. Each marker "id" corresponds to the same nomenclature as the ontological instances for instruments to be processed in context-aware system framework.

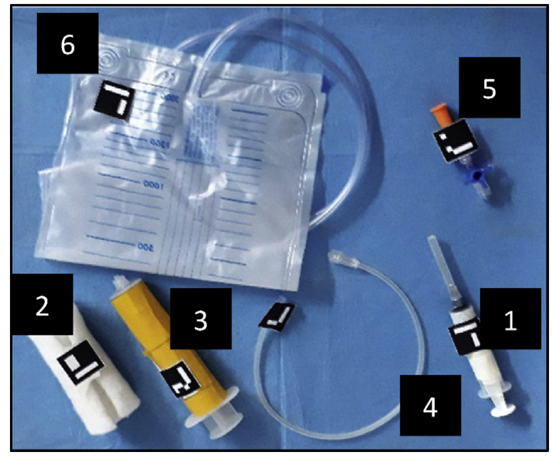

Fig. 4. ArUco markers was used to recognise surgical instruments/materials in surgeon's hands. 10 mL syringe (1) is used to anaesthetise the skin and superficial muscles of the chest region. Surgical swab (2), "betadine swab", is used to sterilise the skin and 50 mL syringe (3) is used to penetrate the intercostal muscles and the pleural cavity to withdraw the fluid. Flexible catheter (4) is used to connect 50 mL syringe with three-way stop-cock (5) and three-way stop-cock is used to change the channel of the withdrawn fluid e.g. to the 50 mL syringe and to the drainage bag (6). The drainage bag is used to collect the pleuritic fluid for further diagnostic examination.

Considering the limitation of Kinect resolution to detect four instruments e.g. three-way stopcock, drainage tube and bag, 10 mL syringe, and flexible catheter, for the full Thoracentesis workflow and the training, we have recognised the instruments in surgeon's hands using ArUco makers. The ArUco markers were captured within 170° field of view and the maximum distance between camera and markers was 50 cm. We used 720p HD video stream input to detect the markers. The ArUco markers detection was implemented using OpenCV [45] library.

2.4.2. Symbolic data grounding and semantic recognition level

(1) *Symbolic data grounding level*, where we extracted features' values as mentioned in Section 2.4.1, e.g. "ratio of height and width of the instrument", and grounded each of the feature's values in the production rules within a certain range. We obtained values of the range by retrieving the geometric features from different view-points for each instrument's surface patches obtained with the particle-filter and the RANSAC-based plane segmentation.

(2) *Semantic recognition level*, where instruments' feature values were mapped with the knowledge on the instruments and dynamically grounded in the ontology through the semantic relations e.g. "hasRatio".

We included a high-level information of instruments, such as the instrument colour is "white", and associated an instance of the instrument in the ontology with the 3D processed data, e.g. "hasCentroidHeightFromTable", obtained from an image sensor inside the ontology through production rules to recognise surgical instruments and materials helpful to accomplish main tasks of Thoracentesis. Each extracted feature's value was published via ROS topics and added as values for the semantic relation, only, and only if, the values satisfied the constraints specified in the rules, to be processed by knowledge module. For example, the betadine swab is of approximately 1 cm height, where instrument's height value in "if" clause was specified using the range e.g. instrument's height is between 0.9 cm to 1.5 cm, and assigned to specific semantic relation e.g. "hasCentroidHeightFromTable". Then the implicit information, e.g. height, of the instrument is obtained by com-

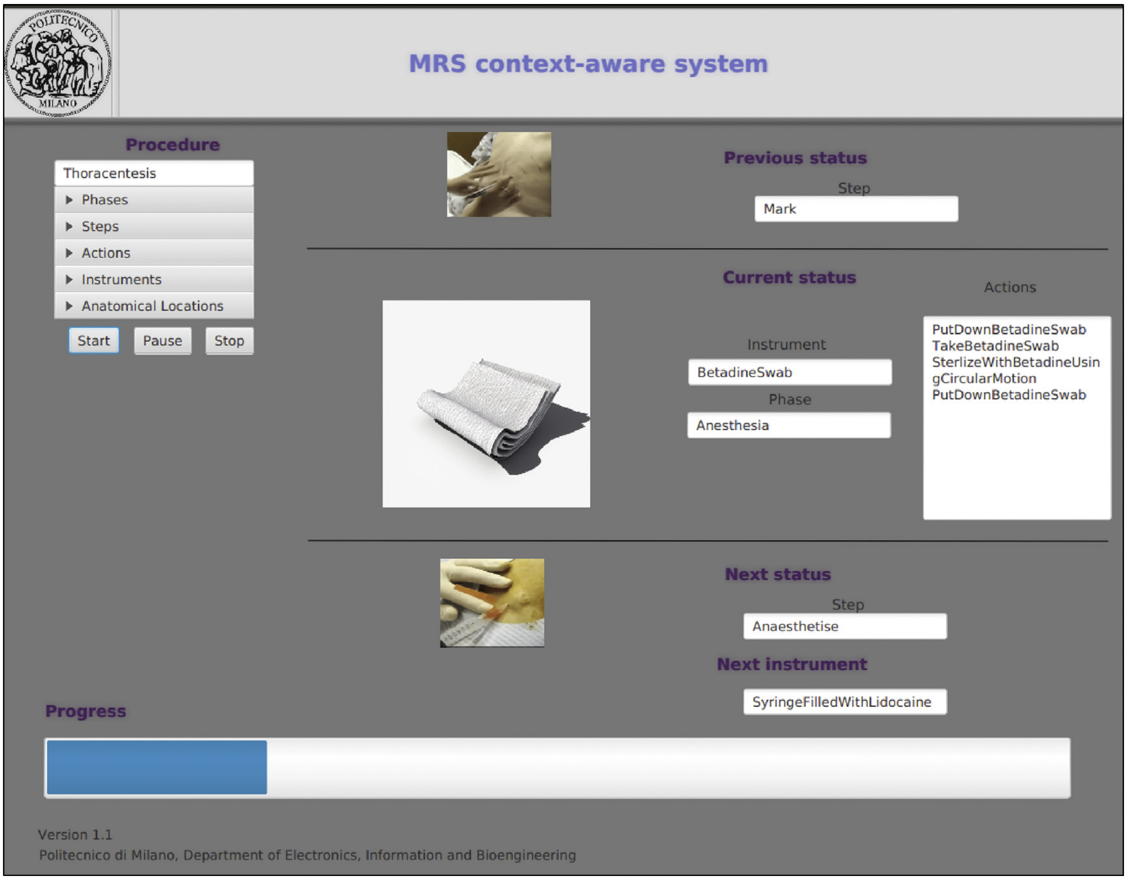

Fig. 5. The GUI provides interaction possibilities with the user, where the user can select the surgical procedure and see different workflow entities, e.g. "Phases", through the buttons in the menu on the left side of the GUI. There are two activities 1) compliance checking, where users verify the "Previous Status", e.g. previous surgical workflow step "Mark", before doing the activities represented in "Current Status"; and 2) surgical execution planning, where the "Current Status" represents the current phase, e.g. "Anaesthesia", of the surgery after detecting the instrument "BetadineSwab" and the surgical actions required to accomplish the specific step using the instrument, and the GUI represents "Next Status", e.g. next surgical workflow step, e.g. "Anaesthetise" and next instrument, e.g. "SyringeFilledWithLidocaine". The next instrument is also visualised, on a separate window, as a segmented surface patch from the surgical stand, obtained using the plane segmentation algorithm (Not shown in the figure). The step of the phase in the "Current Status" is not shown because the step is shown in the "Next Status" during the previous surgical activity for preventing the visualisation of the redundant information.

puting instrument's centroid height from the surgical stand and dynamically included inside the ontology for instances of each surgical instrument. And "then" clause is specified the instrument as a "betadine swab" if the conditions in "if" clause matches with the implicit information dynamically grounded in the ontology.

2.5. Data monitoring and graphical user interface – MRS context-aware system

We developed a data monitoring system and GUI, "MRS context-aware system", as shown in Fig. 5, which constantly monitors the file system database for the changes in ontological instances retrieved by 3D image processing and production rules. While data monitoring interface updates the information online, the information is promptly available to the surgeons in the sterile environment with the help of GUI. The data monitoring system and the GUI were developed using JavaFX [46].

3. Experimental protocol

We performed experiments to validate the ontology and production rules for surgical workflow interpretation. We also checked the framework by experimenting the use of computer vision algorithms for workflow planning and execution. Our experimental scenario was divided into three parts: (i) Ontology validation using the annotated surgical videos; (ii) instrument tracking and recognition in surgeon's hands and on the surgical stand; (iii) Naïve users training on Thoracentesis with the pre-recorded videos and with the intelligent system.

3.1. Ontology validation

We used video annotations data to validate the ontology. For annotating the controlled vocabularies specified in the ontology, which was used to specify surgical process model, we used a set of three videos on Thoracentesis from web resources, e.g. [22] [47] [48]. The videos were annotated frame by frame by two general physicians, with the mid-level expertise in performing Thoracentesis. We asked each clinician to annotate the "phase" of the surgery and an "instrument" in use during a specific instant of time. While annotating the videos, the audio was muted and required controlled vocabulary was explained to clinicians. We used Anvil annotation tool [49] for annotating the surgical videos.

As shown in Fig. 6, we extracted annotation files and saved them in the Comma Separated Value (CSV) format to be read by the framework components e.g. the knowledge module. The framework was provided only with the instrument annotations, as a context for current instrument in use in videos, to recognise the surgical phases. We found the relative frequency, R_p, as shown in

```
Input: Annotated surgical videos
Output: Recognised phases
Function readDatabase
    begin
        Read annotation CSV file
        Annotations {instruments} ← Read line-by-line
    end

Function readAnnotationsFromVideos
    begin
        Read annotation file
        Set framerate (corresponding to the videos)
        for each annotation do
            {
                readDatabase
                return an annotation-instrument in database
            }
    end
Function playVideoAnnotations
    begin
        Read annotation {Phases} ← frame-by-frame phase token
        return an annotation-phase in database
    end
Function phaseRecognitionInOntology
    begin
        readAnnotationsFromVideos
        playVideoAnnotations
        if "phase detected" by framework then
            do annotation-phase == "phase detected"
        else phase not detected
    end
```

Fig. 6. The evaluation algorithm with video annotations for validation of ontology.

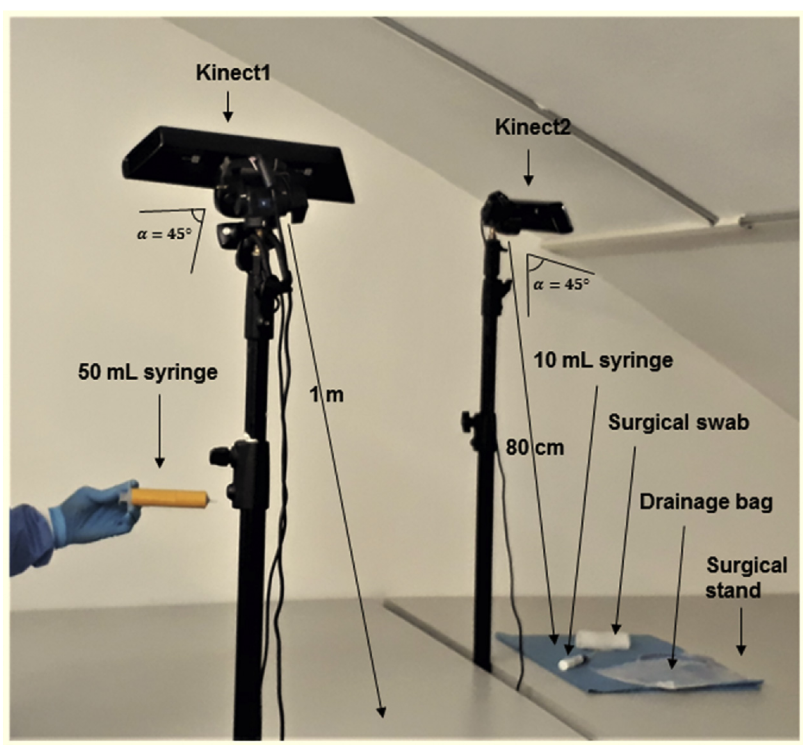

Fig. 7. The experimental setup includes Microsoft Kinects, the surgical stand and surgical materials and instruments. Kinect 1 for instrument detection using tracking was set approximately 1 m away and Kinect 2 for object recognition on surgical stand was set approximately 80 cm away. The figure shows the surgical swab and the 50 mL syringe which were used during the experiments. Both the sensors were kept under the white fluorescent illumination or natural sun-light.

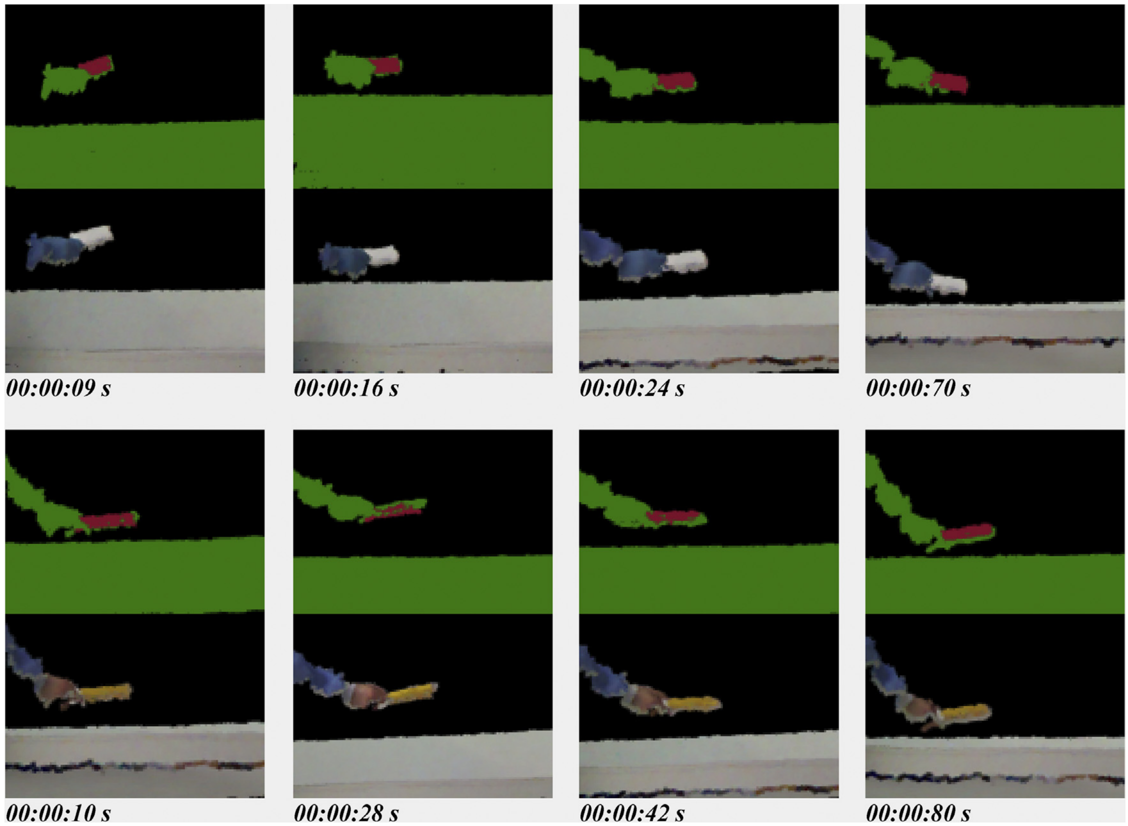

Fig. 8. Tracking results on surgical swab (in the top row) with partial occlusions and 50 mL syringe (in the bottom row without gloves) sequences. The red points represent tracked surgical instrument cluster. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

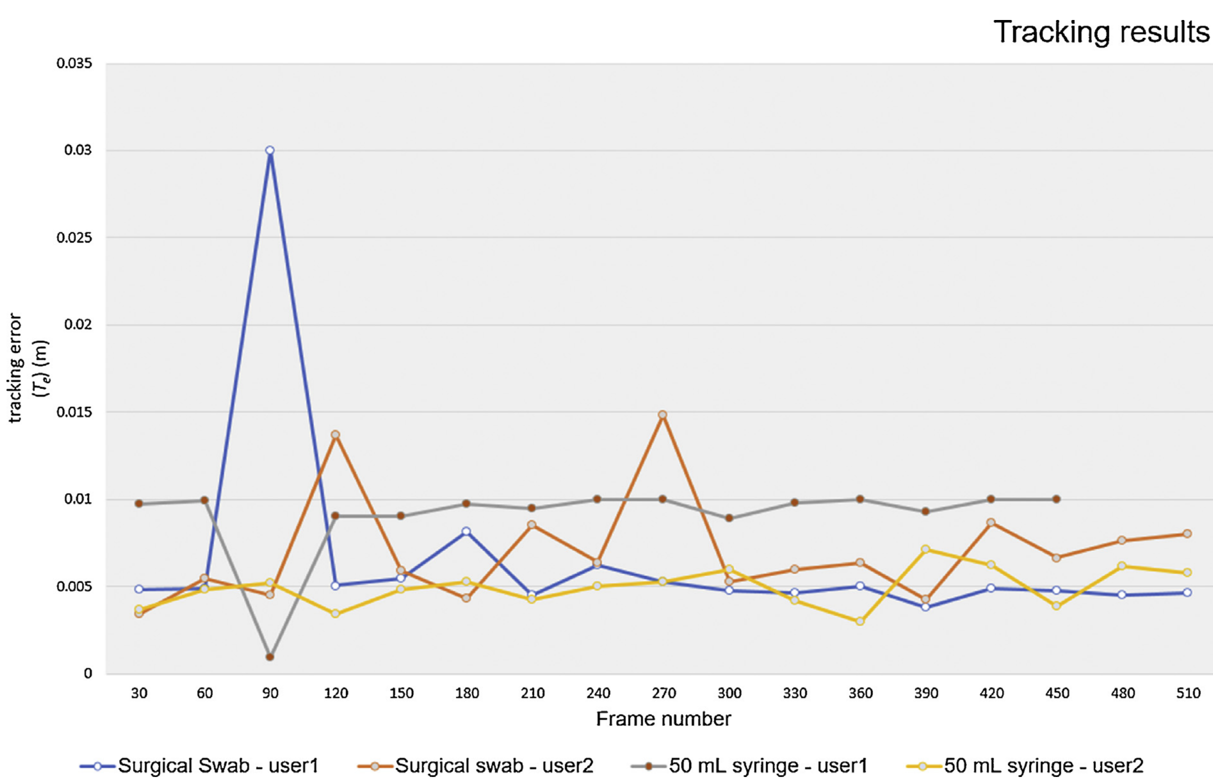

Fig. 9. The chart represents the tracking error during tracking of the instruments, e.g. (a) surgical swab and (b) 50 mL syringe in surgeon's hand, wearing gloves, during the surgical tasks of Thoracentesis.

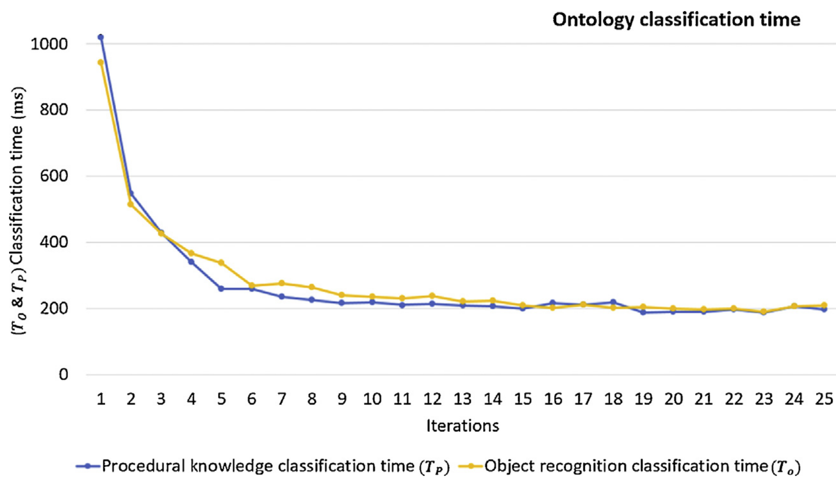

Fig. 10. The figure represents the time required to classify the ontology to infer the instances that contain the contextual information, e.g. instrument recognition in scene, mainly the time, "the object recognition classification time" (T_O), required to compare dynamically retrieved instrument geometric information, e.g. features' values, with production rules to recognise the instrument (yellow line); and after the recognition of an instrument, the time, "the procedural knowledge classification time" (T_P), required to classify the ontology for recognising surgical phases and related information (blue line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

"Eq. (1)", of the inferred surgical phases through the framework with the ground truth phases annotated by the clinicians.

$$R_p = \frac{P_I}{P_T} \tag{1}$$

In Eq. "(1)", P_I represents the number of correctly matched and classified phase instances and P_T represents the total number of phase instances in annotations. We also measured the ontology classification time (T_{Onto}) using Pellet [21] reasoner to measure the time required to classify the subsumption hierarchies in ontology before using it in the framework. The purpose of ontology validation was to check if the ontology has sufficiently covered all the entities and relationships that are required to represent knowledge on Thoracentesis. The video annotations were also used to analyse Thoracentesis to derive the requirements for segmentation and recognition algorithms. We analysed the annotations and found that surgeons were required to change the surgical instrument every approximately 1.8 ± 0.6 min. The phases were changed every approximately 1.0 ± 0.3 min.

3.2. Instrument recognition in surgeon's hands and on the surgical stand

To verify the system performance, we implemented a set of experiments using the set-up shown in Fig. 7. Considering the video annotations input, we tracked each instrument for approximately 2 min, i.e. 3600 frames. We fixed both sensor's viewpoint (Kinect 1 and Kinect 2 in Fig. 7) at approximately 45° to get the maximum coverage of surfaces of the instruments lying on the surgical stand or in the hands. Before each experiment, we obtained an instrument surface patch by segmenting the nearest points, e.g. points with the minimum depth values from camera frame, in the scene point-cloud, hereafter referred as "scene", by removing the plane (e.g. a top of the table) using RANSAC-based plane segmentation algorithm.

To check the feasibility of using the particle filter for tracking surgical instruments in surgeon's hands, we conducted five experiments with two naïve users (Fig. 9). We evaluated accuracy of the particle filter using cloud-to-cloud Euclidean distance, "tracking error", T_e, using the shortest point distance by extracting the point clouds (T_i)of the tracked instruments at every 30 frames. Then, we evaluated extracted point clouds with manually segmenting the instrument point-clouds, as a ground truth (S_i), from the scene point clouds representing the same frame, by extracting the points that fall inside of a 2D polyline once it is projected on screen. We compared performances of the two naïve users and two instruments' tracking accuracy considering an empirical distance threshold of 0.01 m.

$$\|T_e\| = \sqrt{\sum_{i=1}^{K} (S_i - T_i)^2} \tag{2}$$

In "Eq. (2)", K represents the number of nearest neighbours, and S_i and T_i are the source and target points.

We compared the approximate actual duration required to use the instruments in videos with the duration of the respective instruments system tracked. To emulate the real scenario and instrument movements performed during Thoracentesis, we moved the hand in similar patterns during the experiments, where the surgeon holds the betadine swab in his/her hands. Further to that, the system recognises the surgical step and suggests next instrument on the surgical stand.

As the experiments were done in real-time, we repeated experiments for 25 times to report procedural classification time (T_P), which was the time, the framework required to classify ontology for retrieving surgical workflow information, object recognition classification time (T_O), which was the time, the framework required to classify ontology to recognise objects and system data synchronisation errors (S_E), which was the errors incurred during the data monitoring. We correlated, using the Pearson correlation coefficient, object recognition classification time and procedural classification time.

To evaluate the instrument recognition on the surgical stand, we compared our result with the pure data-driven recognition algorithm, template-matching, implemented in our previous research [19]. We ran a total of 10 experiments for each instrument e.g. 10 mL syringe, surgical swab and 50 mL syringe. Each recognised instrument was verified by the instrument recognition result represented on the GUI. We also implemented a real-time interface which constantly displays the recognised instrument's surface patch obtained using the plane segmentation.

Table 1
Surgery phase recognition results.

"Preparation" phase	"Anaesthesia" phase	"Penetration" phase	"Aspiration" phase
80% with $P_T = 3$	100% with $P_T = 5$	65% with $P_T = 5$	100% with $P_T = 5$

3.3. User experiments

We evaluated the training system with 10 naïve participants, Biomedical Engineering graduate students at Politecnico di Milano, who were unware of Thoracentesis procedure. This study was carried out in accordance with the recommendations of our institute with written informed consent signed by the subjects in accordance with the declaration of Helsinki. The mean age of the participants were 24.2 ± 2.3 years. We divided participants into two groups of 5 participants each. Each group was taught Thoracentesis procedure with two different methods:

1) Group (1): Traditional mentor-based training, where a clinician taught Thoracentesis procedure by showing the procedures in three different videos and explaining the procedure concurrently. The clinical background for procedure was briefly explained to participants before starting the training;
2) Group (2): Intelligent system training, where participants were asked to hold the instruments of Thoracentesis, in the sequence of phases of Thoracentesis procedure as suggested by the system. The instruments were recognised as previously described in 2.4.1 to be used in the context-aware system to find the relevant contextual information, which was represented on GUI. The meaning of each ontological entity was explained only if asked by the participants. The clinical background for procedure was briefly explained to participants before starting the training.

After the experiments, both the groups' participants were asked to complete the questionnaire, as shown in Appendix A, which contained the questions about the procedural workflow and contexts, e.g. instrument requirements in different steps etc. We assessed the training efficiency by comparing the number of correct answers between the groups to evaluate their understanding and knowledge of the procedure and workflow. We also compared the time required to accomplish the surgical training and correct answers based on questionnaire evaluation between both the groups.

4. Results and discussion

In this section, we present the results of the individual components of the training system where the results follow the testing protocol mentioned in the Section 3.

4.1. Ontology

The results of the phase recognition and the quantitative validation of ontology, based on grouped video annotations, are shown in Table 1.

Procedural knowledge on "Preparation" phase was inferred with 80% relative frequency $\left(R_p\right)$, while "Anaesthesia" phase was recognised with 100% relative frequency. The model did not infer the correct phases when the instances are repeated in annotations of consequent surgical activities. For example, 50 mL syringe is being used in two different phases of Thoracentesis, "Penetration" and "Aspiration". As there were repeated instances of 50 mL syringe for "Aspiration" and "Penetration" phase, i.e. "Penetration" phase was repeated again after "Aspiration" phase, the model inferred "Aspiration" phase incorrectly during "Penetration" phase. R_p could improve if there are no repeated instances of surgical phases in the workflow and each previous phase was completed before executing the next phase, as we did with the user experiments with marker-based setup. For example, sometimes surgeon has to penetrate the chest wall, "Penetration" phase, in between withdrawing the fluid, "Aspiration" phase, in Thoracentesis workflow. "Aspiration" phase lacks associations with anatomical structures, so we have grounded anatomical structure for this phase as "NoAnatomicalLocation" in ontological assertion box. If the anatomical structure was not grounded, as "Aspiration" is the final phase and information on execution comes after "Penetration" phase, it could hinder the firing of rules for accurately recognising the "Penetration" phase if it is represented again during the workflow execution. The ontology classification time for class hierarchies (T_{onto}) was 357 ms.

Table 2
The time until the system tracked the instruments and the actual approximate time required to track instruments during the procedure.

Instrument/ Material	Instrument cluster number of points	Time (s) (instrument usage time based on video annotations)	Time (s) (based on system tracking)
50 mL syringe	939 ± 71.4	26.8 ± 10.5	240
Surgical swab	1006 ± 76.02	12.2 ± 1.8	240
10 mL syringe	112 ± 53	26.8 ± 4.8	0 (Not tracked)

4.2. Instrument recognition

As shown in Fig. 8, we were able to successfully track surgical swab and 50 mL syringe until 4 min, then we stopped tracking it, which is satisfactory, as shown in Table 2, considering the time required to change the instruments based on video annotations. The system was not being able to track 10 mL syringe because of its small dimension, but this is a problem with the sensor resolution.

As we also performed the experiments with down-sampled point clouds, to increase the speed of algorithm execution, the sample size e.g. segmented instrument cluster size, e.g. 112 ± 53 as shown in Table 2, was much smaller to initialize the tracking algorithm for 10 mL syringe. Further to that, we found that up-sampling of point clouds does not affect tracking results for the above mentioned surgical instruments e.g. 50 mL and 10 mL syringes and materials e.g. surgical swab.

As shown in Fig. 9, the system was able to track surgical swab and 50 mL syringe for 510 frames (around 4 min), taking around 2.13 s for processing each frame. Considering an empirical tracking error threshold of 0.01 m based on visual inspection, the tracker lost the tracking for surgical swab for three times, at frame 90 for user1 and frames 120 and 270 for user2, due to unexpected hand motions but recovered immediately. We were able to track surgical swab and 50 mL syringe with 88.23% and 100% accuracy respectively based on the tracking threshold. The algorithm was not able to track other instruments and materials due to inappropriate instrument surface patches representing the partial surface point-clouds. As mentioned in Section 2.4.1, we were able to recognise all the instruments with 100% accuracy only with ArUco-marker based recognition.

In our previous work [19], we used the template-matching to recognise the surgical instruments on the surgical stand. During our experiments with static point-cloud scene datasets, we achieved 93.3% accuracy in determining 50 mL syringe. The template matching had very high false positive results, as much as 80%, for 10 mL syringe and surgical swab. In our current marker-less scenario experiments for context awareness, we recognised 10 mL syringe, 50 mL syringe and surgical swab with 90% accuracy. The algorithm failed to recognise the instrument only when there was a fault in segmentation of surface patches, which was found to be the segmentation of outlier points, e.g. non-instrument cluster.

We considered classification of a full cycle of instrument and phase recognition as an iteration. As shown in Fig. 10, at initial

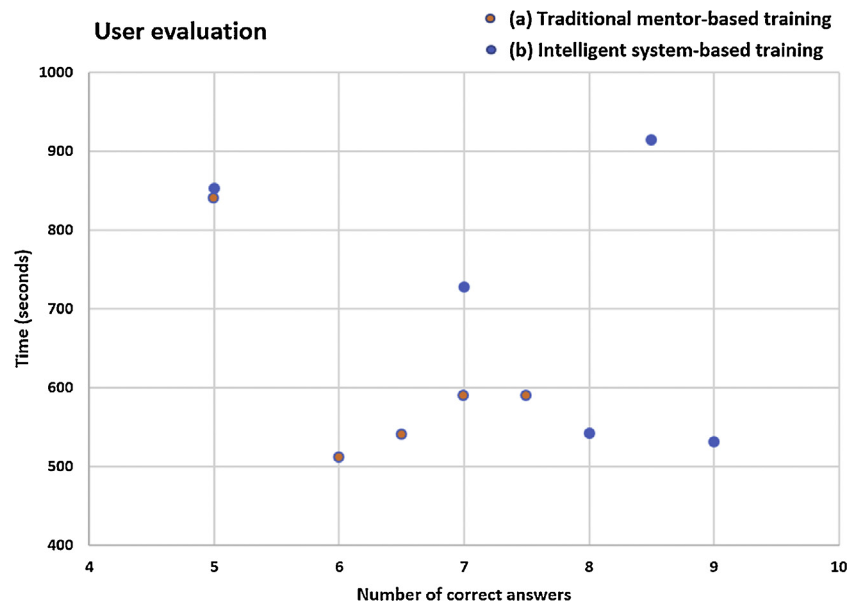

Fig. 11. The chart represents (a) video-based (5 participants) and (b) system-based (5 participants) experiments of Thoracentesis training, showing the number of correct answers and the time required to complete the training (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

iterations, the classification time was higher, but it was gradually improved because initial iterations require to populate data into file system database and the information also need to be represented by the GUI to unfold the contextual information. We measured Pearson correlation coefficient (R = 0.9918, "p < 0.05"). There is a strong correlation between the time required to infer the knowledge to recognise the instrument with the time required to infer the procedural knowledge and contextual information (or vice versa). The direction of causality in these timings show that file system database transactions affect the ontology classification time in a tightly coupled system and system asserts the time synchrony between two different components. During our experiments, we found data synchronisation errors (S_E) during concurrent access to the file system. The main reason was a systematic Java error, which reads the dynamically updating byte streams information for the replacement of recognised contextual information in file database. The systemic error could have been resolved using the relational database structures.

4.3. User evaluation

As shown in Fig. 11, while the participants with traditional mentor-based training gave 6.4 ± 0.96 correct answers on procedure knowledge, the participants who learned the procedure with our approach gave 7.5 ± 1.58 correct answers.

There was also no relationship between the number of correct answers, e.g. understanding of the procedure, and the time a participant took to finish the training ("r = –0.65" with "p < 0.05" for video-based training and "r = –0.46" with "p < 0.05" for intelligent system-based training).

The qualitative user feedback with intelligent system-based training suggested that sometimes it was difficult to follow the number of contextual information represented on GUI. However, most of the users were comfortable to follow the system instructions, especially representative figures, and surgical actions, for learning the surgical workflow. The users commented that it eases their thinking process with the structured representation of surgical information. However, some users suggested that pictorial representation of surgical contexts would have been more helpful than the text-based representation.

5. Conclusion

We presented an intelligent training system for Thoracentesis, which we implemented using context-aware software framework for learning the procedure. We implemented an ontology with inference rules and recognised surgical instruments to make an instrument-recognition driven surgical process training, considering the anatomical locations are already grounded for each surgical activity. In the proposed training system, users read, watch, and intellectualize the individual surgical activities. Our approach allows trainees to accurately assess their own understanding of the procedure and recognise what the new surgical activity would be, for constructing a mental model, based on the identified activity on the surgical phases represented by the system. While current surgical training systems still lack the full cognitive support, the represented work is an important step to introduce a new paradigm for surgical training. Unfortunately, users' evaluation showed only slight improvement in learning and understanding Thoracentesis with the system-based training as compared to traditional one. Other potential benefit is the modular design of the context-aware system framework components, which could be also implemented for advanced robot assisted surgery system architectures for assistive guidance. We researched a new possible set of syntaxes, serialised using SWRL rules that could be helpful with proposed knowledge representation for surgical phase recognition after recognition of instruments. While the previous study was done with the simulation-based setting [19,50], where ontology and inference rules were used as surgical workflow modelling, the developed context-aware system framework allowed real-time processing of data and possibility to extend the framework due to its modular approach.

The major study limitation was detection of small instruments with Kinect, due to its sensor resolution. We were not able to detect four instruments, i.e. three-way stopcock, drainage tube and bag, 10 mL syringe, and flexible catheter. The reasoning mechanism, for object recognition, was also limited to recognise them, due to high variability in extracted features' values and fixed experimental setup. To use the framework for robotically-assisted surgery, automatic recognition of the local patches, comprising anatomical locations and instruments, in laparoscopic videos, could enhance the results and remove the need of grounding the anatomical locations in ontology for surgical steps. As explained in Section 4.1, system would fail with the repeated instances, thus the developed model did not capture the full surgical variability. The data synchronisation errors show that the system components still did not maintain the data transaction consistency, which may be solved by the stream reasoning on ontology e.g. C-SPARQL [51].

As future work, the current system could help retrieving individual surgeon's skills profile as an individual ontology which represents the inferred phase and instruments usage while performing the procedure. Eventually these ontologies could be useful to analyse the surgical skills and user performance. Further work will be aimed at performing extensive system testing involving users with different level of expertise, such as medical students. We propose creating new likelihood functions for particle filtering, generating the automated workflow rules using inductive learning, e.g. First-Order Inductive Learner [52,53] to create individual disease- [54] and procedure-specific [50] surgical process models and testing the system in real-surgical environments where the system retrieves the contextual information to trainees based on the expert performing the procedure. The context-aware system framework could further be enhanced to be used for intention detection [55] in human-robot interaction [56] and for automating and planning [57,58] the robot-assisted surgeries, which will be eventually used in SMARTsurg project as to develop advanced cognition and perception abilities. SMARTsurg project will develop an advanced system for performing Robot Assisted Minimally Invasive Surgery (RAMIS) to reduce surgeon's cognitive load to shorten the training time and to deliver accuracy, safety, reduced procedure time and expanded applicability.

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Appendix A.

Name: ______________________________

Age: __________ *(in years)*

Sex: __________ *(male/female)*

Purpose: *The purpose of this questionnaire is to evaluate your procedural skills and your understanding of different surgical contexts to accomplish Thoracentesis procedure.*

Skills predicted:

A. *Knowledge application: Use your knowledge to answer the questions on Thoracentesis procedure*
B. *Information interpretation: This skill represents your understanding for Thoracentesis procedure*

Instructions: *You will have to complete 12 questions. There may be none, one or more than one right answers*

Questions

1) How many phases are required to complete to accomplish Thoracentesis procedure?

☐ 2 ☐ 4 ☐ 3 ☐ 8 ☐ 6 ☐ 5

If you want to specify any details, ______________________________

2) How many phases require excellent technical skills, e.g. dexterity, to accomplish the Thoracentesis procedure?

☐ 2 ☐ 4 ☐ 3 ☐ 1 ☐ 6 ☐ 5

3) Which is/are the following instrument/instruments is required during the anaesthesia?

☐  ☐  ☐  ☐ 

4) Is 50 mL syringe used after anaesthetising the skin?

☐ True ☐ False

5) Which of the following is true about Thoracentesis procedure?

☐ The procedure is performed on chest cavity

☐ Three-way stopcock is used in anaesthesia phase

☐ Three-way stopcock is used on chest (location)

☐ 50 mL syringe is used in aspiration phase

☐ all above are true

If you want to specify any details,

6) When do you turn the lever of the stopcock to the direction of syringe?

☐ After inserting needle in the chest
☐ For removing the fluid
☐ To insert the fluid
☐ To insert anaesthetic agent

If you want to specify any details,

---

7) How many instruments/material items are required to accomplish Thoracentesis?

☐ 2 ☐ 4 ☐ 6 ☐ 7 ☐ 8 ☐ 10

8) Which anatomical region do you require to anaesthetise during anaesthesia phase?

☐ Skin of the chest
☐ Area of insertion - intercostal space
☐ Area of insertion – paravertebral space
☐ Area of insertion – between eight and ninth rib
☐ Area of insertion – skin

If you want to specify any details,

---

9) Which anatomical region do you need to penetrate to reach the thoracic cavity?

☐ Skin of the chest
☐ Area of insertion - intercostal space
☐ Area of insertion – paravertebral space
☐ Area of insertion – between eight and ninth rib
☐ Area of insertion – skin

If you want to specify any details,

---

10) Which instruments/instrument do you use after using the syringe in anaesthesia and in penetration phase?

☐ Betadine swab
☐ Flexible catheter
☐ 50 mL syringe
☐ Large needle
☐ Three-way stopcock
☐ Information not available

11) How many steps are required to complete Thoracentesis procedure?

☐ 4 ☐ 6 ☐ 3 ☐ 1 ☐ 5 ☐ 8

12) Which are of the following steps corresponding to anaesthesia and aspiration phase?

☐ Anaesthetise ☐ Mark ☐ Turn lever to drainage bag ☐ None of these ☐ All

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