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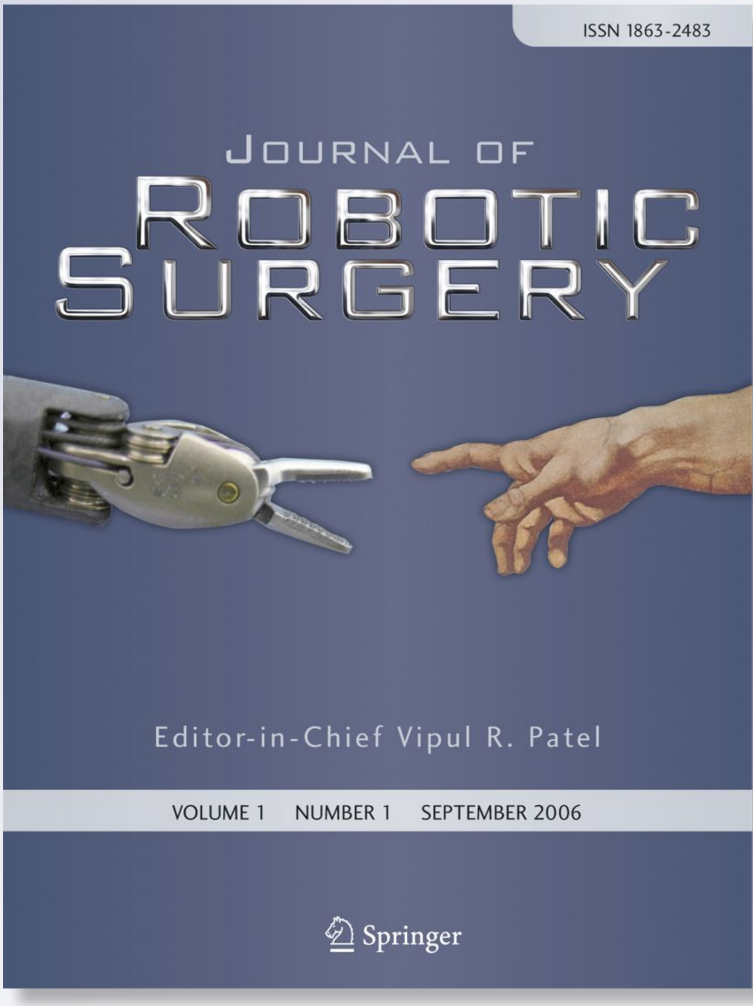

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ORIGINAL ARTICLE

Gestonurse: a robotic surgical nurse for handling surgical instruments in the operating room

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Abstract While surgeon–scrub nurse collaboration provides a fast, straightforward and inexpensive method of delivering surgical instruments to the surgeon, it often results in "mistakes" (e.g. missing information, ambiguity of instructions and delays). It has been shown that these errors can have a negative impact on the outcome of the surgery. These errors could potentially be reduced or eliminated by introducing robotics into the operating room. Gesture control is a natural and fundamentally sound alternative that allows interaction without disturbing the normal flow of surgery. This paper describes the development of a robotic scrub nurse *Gestonurse* to support surgeons by passing surgical instruments during surgery as required. The robot responds to recognized hand signals detected through sophisticated computer vision and pattern recognition techniques. Experimental results show that 95% of the gestures were recognized correctly. The gesture recognition algorithm presented is robust to changes in scale and rotation of the hand gestures. The system was compared to human task performance and was found to be only 0.83 s slower on average.

Keywords Surgical robot · Human robot interfaces · Gesture recognition

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Introduction

Motivation

Recent research assessing verbal and non-verbal exchanges in the operating room (OR) showed that communication failures are frequent; commands are delayed, incomplete, or not received at all, and frequently left unresolved [14]. One study found that 31% of all communications in the OR represent failures [9], a third of which had a negative impact on the patient. Another study found that 36% of communication errors were related to equipment use [10]. Some causes of these errors are team instability (nurses and surgeons who hardly know each other) [7], lack of resources (minimal staffing) and distractions. Poor communication within the surgical team can result in a higher likelihood of instrument count discrepancies among the team, which can indicate surgical instruments retained in the patient's body (sponges and towels are the most common) [8]. Retained instruments can puncture organs and thus cause internal bleeding. The introduction of robots to the OR as assistants to the main surgeon during the surgical procedure has the potential to reduce the number of miscommunications (and their negative effects).

There are three main obstacles to the adoption of robots as an adjunct to the surgical scrub tech in the OR, namely: (1) Communication events can be both verbal and non-verbal (gestures) [10]. While state-of-the-art speech recognition methods achieve high recognition accuracy (over 95%) [19], there is no comparable performance for gesture and body language recognition. (2) Automated anticipatory responses must be customizable to different surgeons or procedures. The automatic system should be able to predict the next surgical instrument required by analyzing context (experienced scrub techs are also known as "mind

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readers"). (3) Gesture-based interfaces have no record in terms of their performance and limitations in the OR (a classic case of the known evil, the standard interfaces, being preferred to the unknown evil that gesture technology represents). The results of the proposed experiments will contribute to the development of better robots and biomedical informatics tools for healthcare environments by improving the understanding of how natural communication and interaction affect the surgical team's performance in the operating room.

Validation and adoption of the proposed technology will enable significant improvements in OR interventions. First, in the case of communication failures, the robotic scrub nurse will deliver surgical instruments to the main surgeon through hand gestures and speech recognition, and will predict the next likely surgical instrument according to the type of procedure (the context) instead of relying on a subjective and variable chain of verbal communications. Timely and accurate instrument delivery to the surgeon can lead to decreased cognitive load and reduced time and effort for surgeons. Second, retained surgical instruments will be avoided by accurate, thorough, and timely monitoring and documentation of instruments used.

Robotic surgical assistants

The introduction of surgical robots into the OR is feasible and can be effective [1, 3, 5, 6, 11, 15, 17, 18]. Borenstein et al. [5] developed a nursing robotic system to assist bedridden patients with simple tasks; the robot has not been validated in the healthcare environment. Treat et al. [17] developed a scrub nurse robot called "Penelope" which passes surgical instruments to a surgeon based on verbal commands. "Penelope" can replace instruments that are unused for a given period of time, can predict the next surgical instrument needed, and can monitor instrument usage to avoid retained instruments. Voice recognition was also used in Carpintero's [6] robotic scrub nurse. The instruments and their position are recognized using machine vision techniques. Both approaches equipped the robot with an electromagnetic gripper to accurately handle the grasp and release of the surgical instruments. Agovic [1] designed a haptic interface and customized gripper for picking surgical instruments in microsurgery, allowing the interaction to be focused at the haptic level (the grasp mechanism mimics the human touch). Yoshimitsu [18] suggested a robotic scrub nurse applied to laparoscopic surgeries that identifies surgical instruments through speech recognition and delivers the instruments according to recognized surgeon's intraoperative actions. The most popular (but expensive) robotic assistant is the da Vinci Surgical System [11]. It can replace the need for a robotic scrub nurse in endoscopic/laparoscopic procedures with a pre-operative plan (not suitable for open/trauma surgery).

Our research takes a novel approach by adopting hand gestures as the main modality of interaction with the robotic scrub nurse in the OR. The rationale of using gestures to interact with the robotic scrub nurse is based on the fact that gestures are currently used in surgery [4]; in addition, gesture interaction is intuitive, easy, fast and touch-less (sterile).

Materials and methods

Overview

Two open surgeries at the Wishard Memorial Hospital (Indianapolis, IN, USA) were observed by the authors to gain insights into current features of surgeon–scrub nurse interaction during surgery and how the use of robotic technologies could potentially improve the effectiveness of the interaction while enhancing the quality of the surgeon's performance in the OR. The first procedure was a trauma surgery resulting from a vehicle hitting a young bike-rider, resulting in vascular ischemic injury. The vascular team repaired the transected blood vessel in the lower leg and confirmed intravascular flow with an angiogram. The other part of the procedure involved the intervention of an orthopedics team to align a fractured leg. This procedure is standard and the surgeon and scrub nurse are part of the same team for most procedures of this type. The scrub nurse was able to anticipate the surgeon's needs in most cases. Only a small set of instruments was required and the total procedure lasted about 4 h. The second procedure consisted of an open abdominal aortic aneurysm (AAA) repair, which is the repair of an overly dilated portion of the abdominal aorta. The basic procedure included dissection and ligation of intervening veins, aneurysm resection and repair, followed by retroperitoneal and abdominal incisional wound closure. In the latter procedure, the number of instruments used was larger, and they were passed to the two surgeons based upon their requests. To summarize the observations, it was found that: (a) surgeons use mostly non-verbal, physical communication (both hand gestures, body posture eye-contact) to interact with scrub nurses when passing surgical tools; (b) scrub nurses often anticipate the needs of the surgeon and assistant when passing the surgical tools; (c) surgeon's eyes rarely leave the surgical site; (d) the time required to pass the instruments is between 2 and 3 s from the request moment (when it is not predicted by the nurse). The robotic scrub nurse system *Gestonurse* (see Fig. 1) developed by the authors can help the surgical team to receive the surgical instruments in a timely manner, quickly, accurately, and without

Fig. 1 The real-time robotic scrub nurse in operation in an OR

changing the visual focus point from the patient, based on hand signals [4].

System architecture

The system architecture of the *Gestonurse* is illustrated in Fig. 2. The streaming video serves as input for the gesture analysis module which is composed of the hand segmentation, fingertip localization and gesture recognition modules. The recognized gesture is interpreted as a command which is passed to the robot. An application module controls the FANUC robotic arm across the network through the Telnet interface with the tool delivery module. Finally, the *Gestonurse* hands the required surgical instrument to the surgeon and awaits the next command. The processing modules in the system architecture (see Fig. 2) are briefly described in the following subsections.

Hand segmentation module

A background model of the scene and a hand color model are first created. The segmentation masks from these models are combined and morphologically processed. The mask of the hand is obtained by choosing the largest blob in the scene and thresholding its area to filter out noise. The contour and convex hull is extracted from the hand mask and passed to the fingertip detection module.

Fingertip localization module

The curvature of the contour is computed at different scales and a point on the contour is accepted as a candidate for a fingertip if it is a local minima and is less than an empirically determined threshold. Due to contour discretization and noise, several candidates satisfying the aforementioned criteria can exist around a fingertip. The candidates close to the convex hull are retained and are clustered together. The centroid of each cluster is then designated as the fingertip.

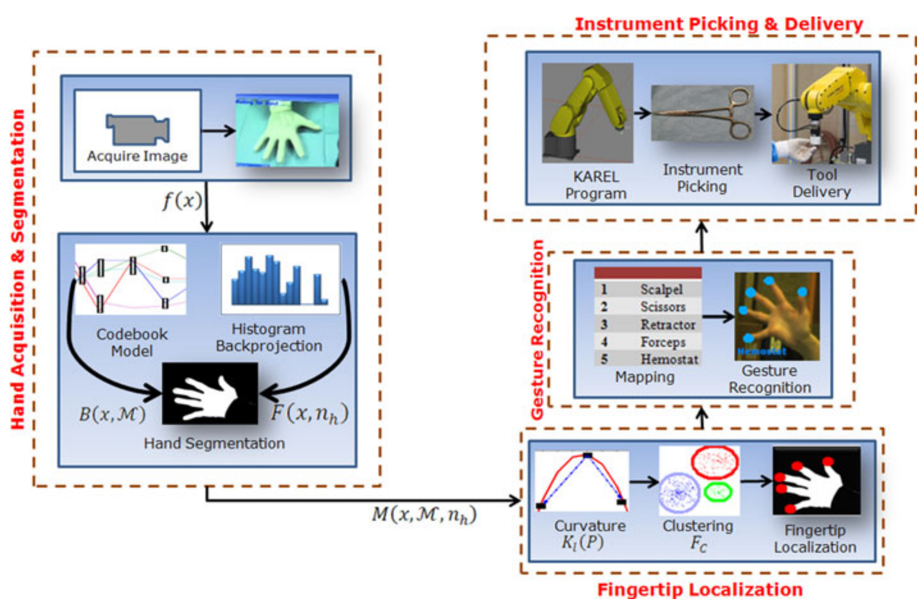
Gesture recognition module

The number of fingertips is bijectively mapped to a set of surgical instruments. Therefore, once the fingertips have been localized and counted, we can recognize the static hand posture performed by the surgeon.

Tool delivery module

The FANUC robot is programmed using KAREL, a scripted language used to control FANUC robots. The corresponding KAREL program is selected for the

Fig. 2 System architecture



recognized gesture and is executed on the FANUC controller over the Telnet interface.

The robot proceeds to pick the instrument from its predefined position and pass it to the surgeon and then returns to the starting position.

Gesture analysis

Hand segmentation

The codebook algorithm [12] is used to model a background scene based on multiple samples of the background. The algorithm observes the *YUV* values of a pixel during the training phase and creates/expands existing sets in *YUV* space to cover the values observed over time. Since the size of a set is limited, it cannot expand to cover all the possible values of *YUV* and thus a new set is created.

The sets or codebook entries constitute the learned codebook model $\mathcal{M}$ which we use to create a mask to segment the hand from the scene, i.e. a foreground pixel or a pixel which cannot be explained by $\mathcal{M}$. Let the *YUV* values of a pixel x be $f(x)$ such that $f^Y(x)$, $f^U(x)$, and $f^V(x)$ represent the *Y*, *U*, and *V* components of x respectively.

Let a codebook entry be $R \in \mathcal{M}$. A codebook entry is associated with 6 values, the upper and lower bounds for each component in $f(x)$, i.e. R_U^Y and R_L^Y, respectively for the *Y* component. Therefore, *R* can be defined as the set of points in *YUV* space which lie within the aforementioned bounds for each component of $f(x)$.

$$R = \left\{f(x) : R_L^k \leq f^k(x) \leq R_U^k \text{ for } k \in \{Y, U, V\}\right\} \tag{1}$$

Hence, we can generate a mask *B* for the background pixels using the codebook model and the *YUV* values of a pixel *x* as follows:

$$B(x, \mathcal{M}) = \begin{cases} 0 & : \quad f(x) \notin R \, \forall R \in \mathcal{M} \\ 1 & : \quad \text{otherwise} \end{cases} \tag{2}$$

A foreground mask (see Fig. 3a) based on the hand color is also generated and stored as a histogram n_h. Histogram back-projection [16] is used to determine the probability $P(x, n_h)$ that a pixel belongs to the hand color histogram n_h. A foreground mask $F(x, n_h)$ (see Fig. 3b) is generated by thresholding this probability with a constant γ:

$$F(x, n_h) = \begin{cases} 1 & : \quad p(x, n_h) > \gamma \\ 0 & : \quad \text{otherwise} \end{cases} \tag{3}$$

The combined hand mask *M* (see Fig. 3c) is obtained as follows. (Note that $\overline{B(x, \mathcal{M})}$ denotes the logical negation of the output of *B*.)

$$M(x, \mathcal{M}, n_h) = \overline{B(x, \mathcal{M})} \cap F(x, n_h) \tag{4}$$

A morphological closing operation is used to clean *M* and remove any spurious mask elements. Additionally, the largest blob in the scene is selected after its area is thresholded and the contour *C* and convex hull *H* is computed for use in the fingertip detection subsystem.

Fingertip detection

We build on the finger detection method used by Argyros et al. [2]. Their curvature measure $K_l(P)$ is modified so that it lies in the range [0, 1]. Let P_1, P and P_2 denote successive points on the contour and let θ be the angle between vectors $\overrightarrow{P_1P}$ and $\overrightarrow{PP_2}$. Also, let P_1, P and P_2 be separated by *l* points. Then, the curvature measure is defined as:

$$K_l(P) = \frac{1}{2}(1 + \cos\theta) \tag{5}$$

The parameter *l* is used to detect fingertip candidates and valleys at several scales by constructing a set *L* of detected local minima on the contour in $K_l(P) : P \in C$.

Then, the candidate set *S* of finger tips is created from local minima, thresholded by the curvature with κ:

$$S = \{P \in L : K_l(P) \leq \kappa\} \tag{6}$$

Furthermore, the local minima can be effectively detected by distinguishing valleys between fingers from the fingertips using the convex hull of the whole hand (see Fig. 4a).

Fig. 3 **a** Background mask B. **b** Foreground F. **c** M

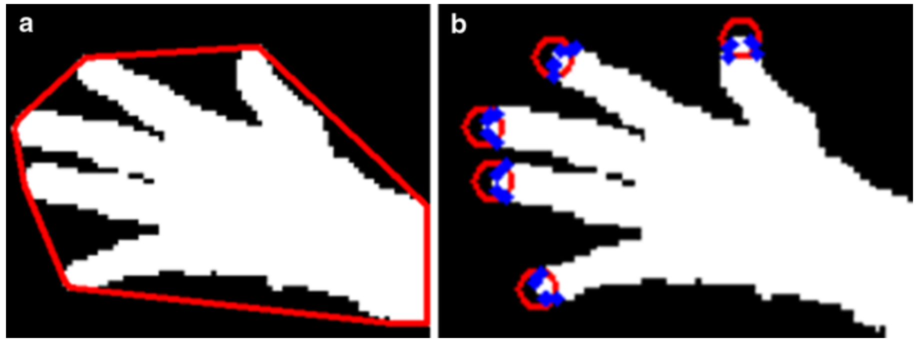


Fig. 4 **a** Convex hull. **b** Clustering of candidate fingertips

We empirically found that the fingertips lie close to the convex hull H. Let $NN(P,H)$ return the nearest neighbor of P in H, and let d be the threshold on the Euclidean distance from the convex hull. We refine the candidate set S based on the proximity to the convex hull H and define F_C as:

$$F_C = \{P \in S : \| P - NN(P,H) \|_2 \leq d\} \tag{7}$$

Discretization of the contour or imperfect hand segmentation can cause F_C to contain several points around the true fingertip since several local minima satisfy the criteria in Eqs. 6 and 7. Therefore, points in F_C which are close to each other or whose separation distance is thresholded by a constant δ are clustered together and a representative point is chosen as the fingertip.

The ordering of points known from the contour C is used to improve clustering performance. Let $\mathrm{P_a}$ and $\mathrm{P_{a+1}}$ denote two adjacent points on the contour C and let a set of contiguous points on C from $\mathrm{P_a}$ to $\mathrm{P_b}$ inclusive be defined as:

$$\mathrm{P_{ab}} = \{\{\mathrm{P_a}, \mathrm{P_{a+1}}, \mathrm{P_{a+2}}, \ldots \mathrm{P_{b-1}}, \mathrm{P_b}\} : a \leq b\} \tag{8}$$

Then, the candidate points are grouped into the set of clusters T as follows:

$$T = \{\mathrm{P_{ab}} : \| \mathrm{P}_i - \mathrm{P_{i+1}} \|_2 \leq \delta \text{ for } a \leq i < b\} \tag{9}$$

The size of each cluster in T is thresholded and the representative point for each cluster is its centroid (see Fig. 4b).

Posture recognition

Figure 5 displays the localized fingertips on a hand contour. The aforementioned algorithm is capable of localizing fingertips and determining local minima which satisfy the constraints in Eqs 6–9. Five poses are determined using the fingertip detection method and are mapped to surgical instruments (see Table 1).

Tool delivery robotic system

The FANUC LR Mate 200iC (see Fig. 6a) robotic arm is used to pass surgical instruments to the surgeon. Teach-pendant (TP) programs were recorded for the delivery of each surgical instrument. The KAREL program interacts with the gesture analysis module over the network through a Telnet interface. The complete system is illustrated in a flowchart (see Fig. 7). A router is used to connect the PC, FANUC robot and network camera. Additionally, a latex-encased magnetic gripper is used in order to maintain instrument sterility (see Fig. 6b) when the robot hands the instrument to the surgeon.

Experiments

Experiment 1: instrument picking performance

Forceps, hemostats and scissors-type instruments may be required in large quantities (300–400) and are usually placed close together (see Fig. 8). High precision and reliability is required to accurately deliver instruments packed close together in small clusters.

This scenario is tested in the following experiment. The distance between the centerlines of two instruments in a cluster is defined as λ. The performance of the system in

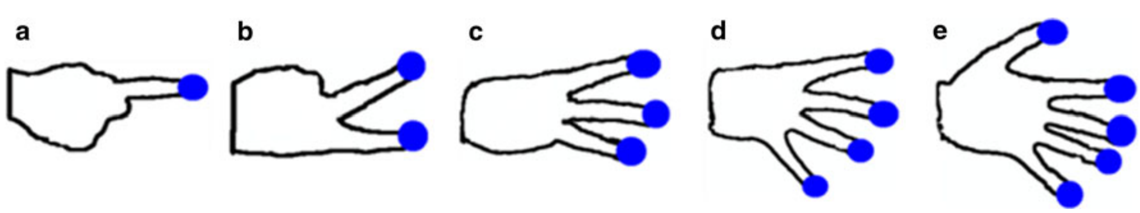
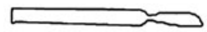
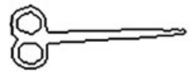
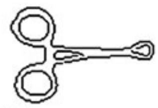
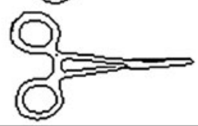


Fig. 5 Fingertips in the gestures for **a** scalpel, **b** scissors, **c** retractor, **d** forceps, **e** hemostat

Table 1 Gesture mapping

Name	Instrument	Gesture
Scalpel		
Scissors		
Retractor		
Forceps		
Hemostat		

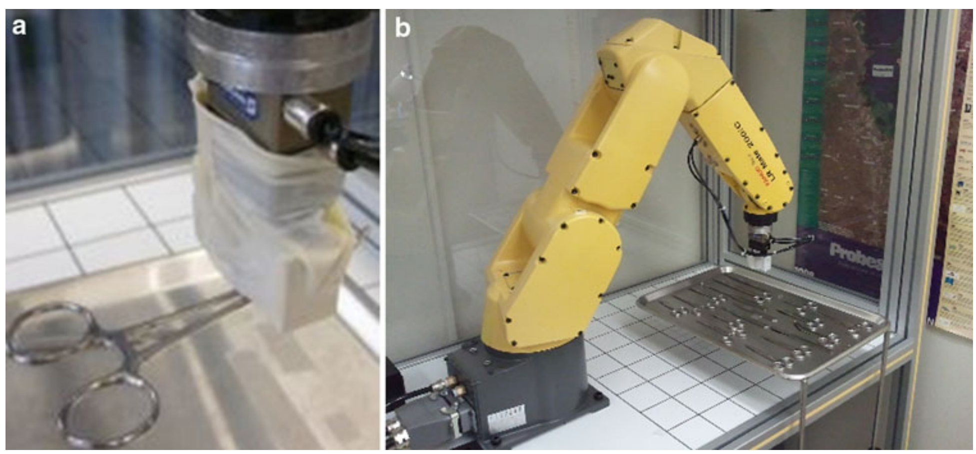


Fig. 6 **a** Gripper with instrument. **b** FANUC LR Mate 200iC

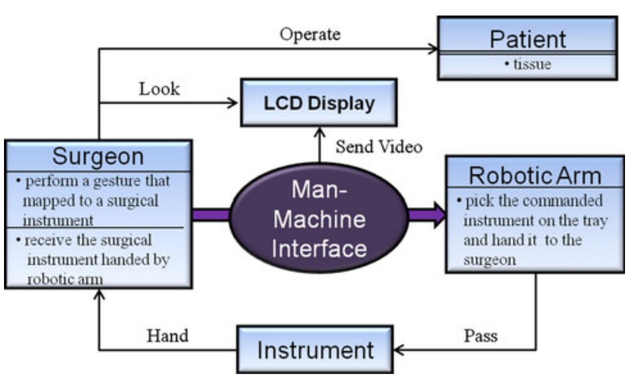


Fig. 7 System flowchart

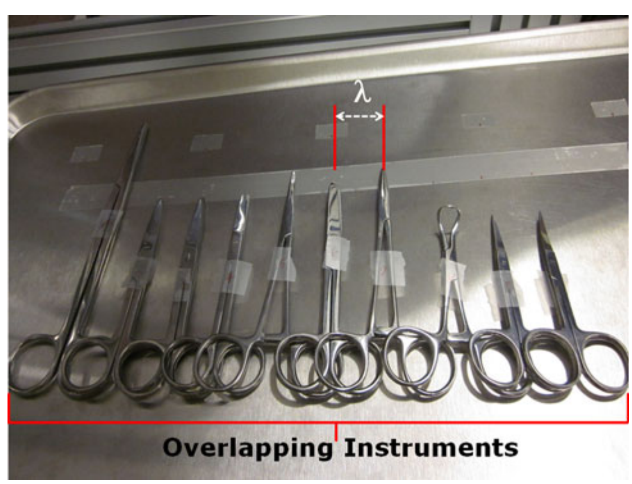


Fig. 8 Instrument set-up showing λ

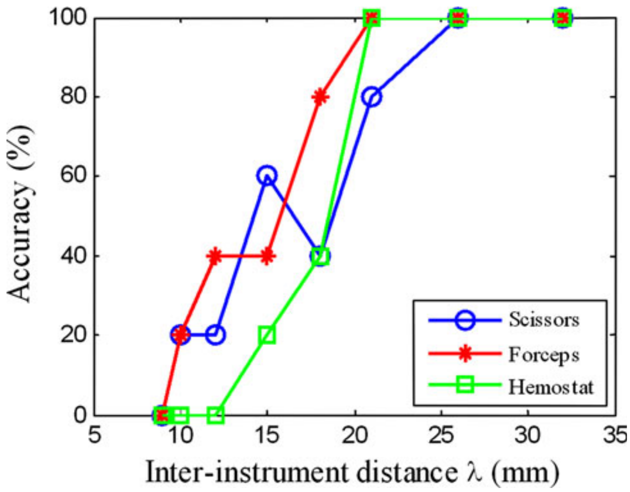


Fig. 9 Instrument picking accuracy versus inter-instrument distance (λ)

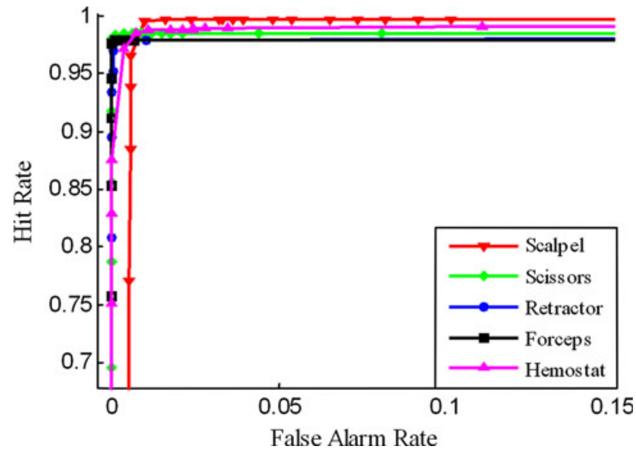


Fig. 11 ROC curves for different κ fingertip detection algorithm

picking different types of surgical instruments clustered in a small area of the Mayo stand is studied by recording the picking accuracy of the *Gestonurse* with respect to λ per instrument type.

The results are displayed in Fig. 9, where a picking and delivering task is evaluated. The number of trials which resulted in successful delivery was recorded from ten trials per instrument. It is counted as an error when the gripper of the *Gestonurse* either does not pick the instrument, drops the instrument before reaching the surgeon's hand, picks more than one instrument or picks the wrong instrument.

Experiment 2: gesture analysis performance

The gesture analysis database consists of 300 cluttered background images (see Fig. 10 for samples) for training the codebook model, and 1,000 RGB images of size 720×480 pixels per gesture performed by a single user. The dataset used for testing consists of 2 databases captured from users of different hand color, shape and size.

Each user was instructed to keep their hands parallel to the image plane and move their hands in the image plane. This resulted in images of static pose gestures at different scales, rotations and positions.

The curvature κ was varied to obtain the ROC curves (see Fig. 11) for each gesture and for fingertip detection across all gestures. The confusion matrix in Table 2 was generated with $\kappa = 0.30$ over our database of static hand pose gestures. We use the ϕ class to represent cases where zero or more than 5 fingertips were detected. On average, the recognition accuracy was found to be 94.65%.

Experiment 3: system speed comparison

The speed of the complete system (*Gestonurse*) was compared to that of a person passing the instrument (human) and when a keyboard is used to request the required instrument from the robot (KRNS). Figure 12

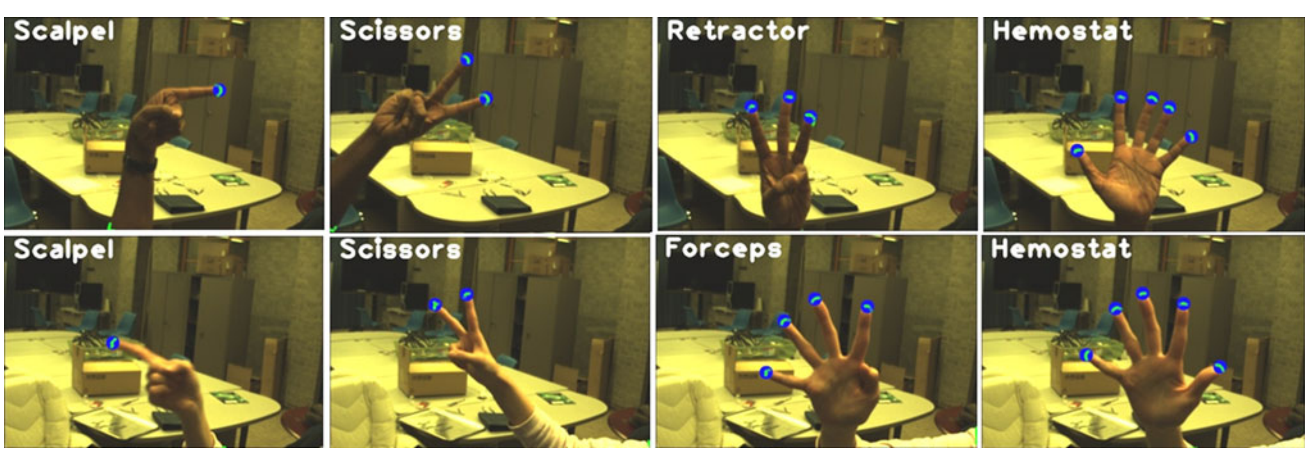


Fig. 10 Samples from the database with correct fingertip detection

Table 2 Confusion matrix (%) for $\kappa = 0.30$

	Scalpel	Scissors	Retractor	Forceps	Hemostat	ϕ
Scalpel	97.15	2.30	0.25	0	0	0.3
Scissors	3.20	96.75	0.05	0	0	0
Retractor	0	7.30	92.70	0	0	0
Forceps	0	0	8.55	91.40	0.05	0
Hemostat	0.1	0.7	1.65	2.20	95.25	0.1

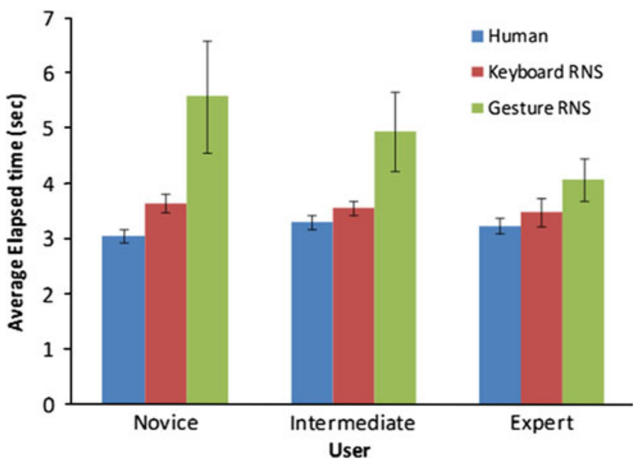


Fig. 12 Comparison of different systems with the mean and 95% CI

displays the mean system time for each class for the aforementioned systems as well as the 95% confidence intervals (CI).

The experiment was conducted as follows. An arbitrary sequence of instruments was randomly generated and used as the test sequence for all the subjects and all the systems being compared. The name of each instrument from the test sequence was displayed to the subject who requested the instrument.

The system time is defined as the time elapsed between the instrument name and the subject receiving the instrument and was recorded for each system which was compared (*Gestonurse*, KRNS and human).

The human system was simulated by the subject saying the name of the instrument out loud and a person handing over the instrument from the Mayo stand (the person does not see the displayed name from the test sequence).

The KRNS is the same as the *Gestonurse* except a keyboard interface replaces the gesture interface. Each instrument is represented by an alphabet (most of the time, the first letter of the instrument name) and the subject sees the instrument name and presses the appropriate key on the keyboard.

The test sequence has 25 instruments, and three classes (novice, intermediate and experienced) of three users per class were studied. Each class corresponds to the amount of experience with the *Gestonurse*. A novice has little experience with the system and is allowed to test a few gestures before starting the trials. The intermediate and experienced users are allowed to "warm up" with a few gestures as well and have already been tested as a novice and intermediate user respectively.

Experiment 4: economy of movements

A longitudinal midline incision was performed on the simulated abdominal wall to enter the peritoneal cavity without damaging the internal organs. The wound was then closed using a blunt needle ensuring that no tissue is caught up by the suture material. All the instruments required to complete this task were delivered by a robotic surgical manipulator directly to the surgeon. The instruments were requested through voice and gesture recognition. The robotic system used a low-end range sensor camera to extract the hand poses and for recognizing the gestures. The instruments were delivered to the vicinity of the patient, at chest height and at a distance reachable by the surgeon. Task performance measures for each of three abdominal incision and closure exercises were measured and compared to a human scrub nurse instrument delivery action. Having a robotic scrub nurse deliver the surgical instruments always to the same position, which is close enough to the surgeon, but not too close to cause collisions, increases both the habitual movements (movement trajectories designed, through accurate repetition, to become a habit) and the continuous movements (movements patterns which are smooth, and avoid drastic changes in direction). A proxy measure for these parameters is the variance among the trajectories used to pick the instrument, or the picking location itself. The purpose of this experiment is to determine whether a robotic scrub nurse can deliver the surgical instruments such that the economy of movement is maximized.

Results

Experiment 1: instrument picking performance

In Experiment 1, it was observed that the robot can reliably pick the instrument from the Mayo stand and hand it to the user when instruments are separated by at least 25 mm (see

Fig. 10). Additionally, the magnetic gripper has been shown to be effective at picking instruments even if they are stacked close together.

It is apparent that there exists an intuitive relationship between the degree of packing instruments in a small area of the Mayo stand (or equivalently the inter-instrument distance λ) and the accuracy of the picking and delivery task. In addition, there is a link between the shape of the instrument and the overall performance of the task. It was seen that picking instruments with smaller areas, like forceps, has higher accuracy, but the picking performance for the hemostat type of instrument is worse due to its larger area.

Since larger portions of instruments overlap when instruments are packed close together, the accuracy of task delivery was impacted because events such as a falling or an unpicked instrument occur, thus resulting in interference between adjacent instruments.

Experiment 2: gesture analysis performance

Experiment 2 showed that the fingertip detection algorithm achieved a very high average hit rate of 98.17% with a false positive rate of 0.63% at $\kappa = 0.30$. The lower average gesture recognition accuracy of 94.65% is explained by out-of-plane rotations (see Fig. 13) in the database. Since the curvature changes dramatically during these rotations, the fingertip detection algorithm fails to detect the fingertips.

In practice, users learn to keep dramatic out-of-plane rotations to a minimum and thus achieve high gesture recognition accuracy. This is apparent from the decreasing average system time as users gain more experience (see Fig. 12).

Experiment 3: system speed comparison

Experiment 3 measured the time elapsed between six experienced users requesting the instrument and receiving it. When using the *Gestonurse* the delay was 4.06 s on average, as opposed to 3.23 s when a human assistant passed the instruments (refer to Fig. 12). The robotic system is only 0.83 s slower than the human system. This result shows that further incremental improvements in the *Gestonurse* implementation can result in a fully operational system in the OR.

Table 3 P values for Levene's and Brown–Forsythe tests

Statistical test	P value
Levene	0.000022
Brown–Forsythe	0.000905
ANOVA	1.2308e-008

Experiment 4: economy of movements

We used the following statistical tests to compare the picking points of the human nurse and the *Gestonurse*.

Equality of variances

The equality of variances in samples of instrument picking points was tested. If the resulting P value is less than a critical value, these tests reject the null hypothesis that the population variances are equal and conclude that there is a difference in the variances in the population. The Euclidean distances from the center of the cluster is used to determine the P values for Levene and Brown–Forsythe tests (Table 3).

Analysis of variances (ANOVA)

One-way ANOVA was conducted on the Euclidean distances from the center of the cluster and was used to compare the means of distances from the center of each cluster (see Fig. 14).

Usability tests

An initial prototype of the system was introduced in the operating room of the Large Animal Hospital at Purdue University for a validation test. At the time that the experiment was conducted, the prototype only included gesture recognition and worked at 5% of the current speed. A mock surgery was performed where the surgeon interacted with an

Fig. 13 Examples of out–of-plane rotations

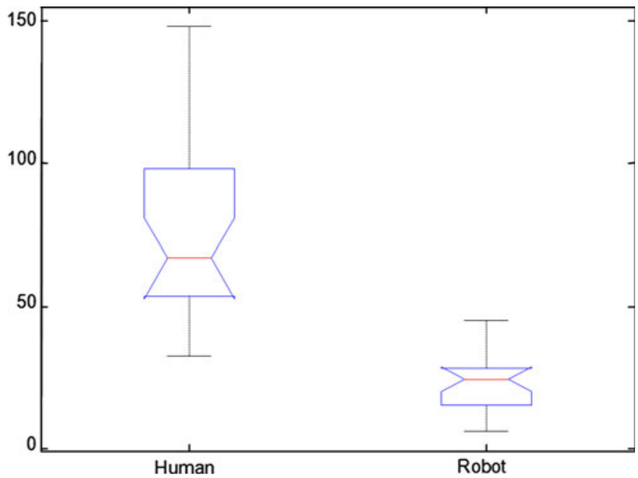


Fig. 14 Box plot for picking/delivering position coordinates

initial prototype of robotic scrub nurse. Three usability tests were conducted during this mock surgery. The first involved a contextual interview, where the authors observed and listened to the main surgeon while he performed the task. The evidence found indicated that the main surgeon must not be distracted, his hands need to remain close to the patient, and errors in communication can result in health risks. The second test was an individual interview. The main points found in a discussion with the surgeon were (a) the need for a faster robot (the prototype tested was 5 s slower than a nurse); (b) the need to retrieve numerous different instruments to give to the surgeon and put instruments back on the Mayo stand numerous times; (c) speech recognition will increase the flexibility and naturalness of the interaction. In general the surgeon recommended a more sophisticated and flexible system that must perform as well as an experienced scrub nurse. At the end of the entire operation procedure, the main surgeon filled in a questionnaire to measure overall satisfaction and usability. The questionnaire used a five-point scale to assess overall satisfaction, similar to the ASQ created by Lewis [13]. The questionnaire included questions assessing ease of use, learnability, intuitiveness, precision and flexibility. The main surgeon found that *Gestonurse* was moderately easy to use, remember and learn. He found it moderately comfortable and safe. He believed the concept was viable but indicated that the *Gestonurse* would have to be more complex and sophisticated to be usable in the OR room; for example, up to 100 instruments would have to be managed by the *Gestonurse* to be effective.

Discussion

A robotic scrub nurse capable of handling and passing surgical instruments, called *Gestonurse*, was tested during a mock surgical procedure at the Large Animal Hospital at Purdue University. This robot uses real-time hand tracking and recognition based on fingertip detection and gesture inference. In an in situ experiment, the robot passed the surgical instruments to the main surgeon effectively and safely, without interfering with his focus of attention. In addition to allowing natural interaction with the surgeon, *Gestonurse* provided the following features: (a) ease of use—the robotic system allowed the main surgeon to use his hands which are the surgeon's standard working tool, (b) natural interaction—nonverbal commands issued through hand signals are fast and intuitive, therefore the robot should interact quickly and still be reliable (currently, *Gestonurse* can process images in real-time, can recognize speech commands, and handle the surgical instruments to the main surgeon within 4 s), (c) an unencumbered interface—the proposed robotic system does not require the surgeon to wear markers nor to attach microphones, and (d) reliability—the hand gestures are recognized with an accuracy of 94.65%, and the robot can pick instruments when they are as close as 25 mm from each other. The results of a satisfaction questionnaire and two usability tests (contextual and individual interviews) showed that *Gestonurse* has the potential to be adopted in the OR to pass surgical instruments to the main surgeon in a safe and accurate manner, releasing the human scrub nurse from this arduous and time-consuming task. Future work includes the prediction of the next surgical instrument to be used, adoption of dynamic gesture interaction according to standard signs used in surgery, and consideration of more powerful features to find the hand, classify the gestures and increase the capacity to manage numerous instruments. To decrease the response time, a faster robot will be necessary. A more exhaustive comparative experiment between our robotic scrub nurse and a human scrub nurse in the OR setting is planned for the future.

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Conflict of Interest None.

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