

A Multi-Robot Cooperation Framework for Sewing Personalized Stent Grafts

Abstract—This paper presents a multi-robot system for manufacturing personalized medical stent graft. The proposed system is a modularized system with three major components: a (personalized) mandrel module, a bimanual sewing module and a vision module. The mandrel module incorporates the personalization of the product, while the bimanual sewing module adopts a learning-by-demonstration approach to transfer human hand sewing skills to the robots. The human demonstrations were firstly observed by the vision module, and then encoded using a statistical model to generate the reference motion trajectory. During autonomous robot sewing, the vision module plays the role of coordinating multi-robot collaboration. Experiment results show that the robots can sew with sub-millimeter accuracy and adapt to multiple personalized stent designs. The proposed system is generalizable to other manipulation tasks, especially for mass production of customized products and where bimanual or multi-robot cooperation is required.

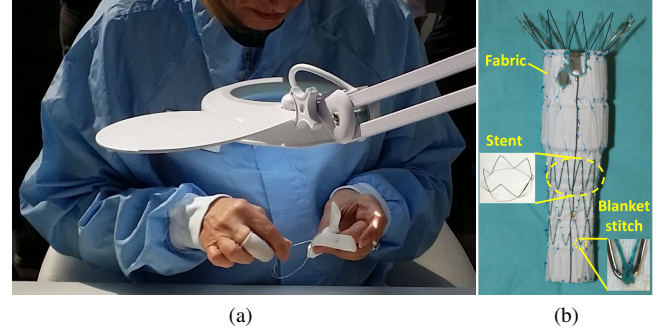


Fig. 1: (a) Hand sewing of a personalized stent graft. (b) A personalized stent graft.

1 INTRODUCTION

The latest development of robotics, sensing and information technology is driving the future of Industrial 4.0. One of the key concepts is smart factories: factories with flexible production lines to produce quality products tailored by customers requirements [1]. Different from the current practice, a smart factory requires a single flexible production process to finish multiple products with different designs. Such a scheme needs to be equipped with: 1) smart machines or robots that can program itself automatically according to customized designs; 2) self-optimizing mechanisms that can react to changing conditions during the production process; 3) real time sensing to monitor and guide the process to ensure accuracy.

In this paper, we propose a multi-robot manufacturing scheme for mass production of personalized medical stent grafts. A stent graft as shown in Fig. 1 is a medical device commonly used during endovascular surgery for Abdominal Aortic Aneurysms (AAA). Vascular disease is a major contributor to cardiovascular deaths in the Western world [2]. The proposed system incorporates personalization, learning and adaptation combined with real-time vision. It takes the advantage of the latest additive manufacturing process for making patient specific models. To reduce the complexity of robot motion planning, the repetitive part of the task is separated from the personalized part, and is assigned to different robots. The entire process is monitored by a real-time vision system, which communicates and servos the robots according to different steps of the production process.

2 RELATED WORK

Research into automated personalized manufacturing has received extensive interests in recent years. Most studies focus on the high level design of the system, such as incorporating wireless

network and cloud computing in factories [3], using big data for product modelling and customization [4], and automating the demand and supply network [5]. Extensive research on automated sewing has also been performed in the textile industry. Most of the existing research has been focused on augmenting the capability and intelligence of conventional sewing machines. Research has been carried out on the redesign of sewing heads that are capable of sewing from a single side of the fabric, different from conventional sewing requiring mechanisms at both sides of the fabric. These designs allow for sewing on complex 3D surfaces. For example, KSL Keilmann (Lorsch, Germany) has developed various 3D stitching systems incorporating single sided sewing heads onto KUKA manipulators. Other topics in this field include bimanual robotic sewing [6], fabric tension control, and edge tracking [7]. To cope with environmental changes during the sewing process, various control strategies have been implemented, including fuzzy logic controllers [8], hybrid position/force control [6], and leader/follower control strategies [9].

In this paper, we focus on a high-value medical device manufacturing challenge: how to enable robots to produce a variety of product designs and to coordinate a learning based multi-robot cooperation task. The proposed system uses a time-consuming process of stent graft sewing as the exemplar, which is a challenging task as hand sewing involves dexterous manipulation of the needle, fabric and thread. The personalized stent graft is currently handcrafted with stents manually sewn onto the fabric (Fig. 1), which requires an adaptive way to manipulate the sewing needle according to stent locations. Despite the speed of conventional sewing machine systems, they lack the ability to adapt to different free-form 3D geometries.

As bimanual sewing involves complex coordinated motions,

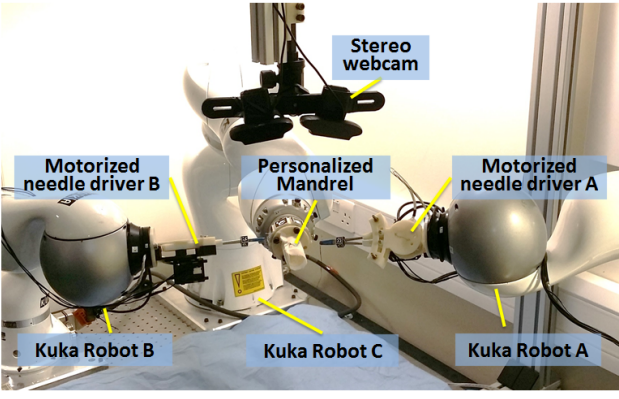


Fig. 2: An overview of our system setup

we have adopted a learning by demonstration approach. Learning by human demonstration has been studied for many industrial applications, such as welding and assembling [10]. Existing methods range from the simple record-and-replay methods to more sophisticated approaches of incorporating visual servoing to cater for positional variation and different poses of grasping. The look-and-move visual servoing method [11] can be used to increase task accurately and adapt to changing environments. Furthermore, it effectively compensates the kinematic errors of the robots.

However, the effectiveness of vision-based manipulation also relies on the accuracy of tool tracking and detection [12]. In medical suturing, small objects such as needles are difficult to track by camera. To this end, Iyer et al. [13] proposed a single-camera system for auto-suturing with a monocular pose measurement algorithm [14]. A 3D stereo system was proposed [15] to improve the accuracy of aligning the needle with the target stitching point. In this paper, we present a robust needle detection algorithm. Fig. 2 illustrates the major components of the proposed manufacturing system. The main contributions of this work include:

- 1) A modularized multi-robot system cooperating under visual guidance;
- 2) A novel hardware design (mandrel) to cater for personalized product design and handle fabric deformation;
- 3) An easy-to-use method for users to demonstrate delicate bimanual tasks;
- 4) A robust needle pose estimation algorithm with shape and pose prior;
- 5) An adaptive trajectory computation method to meet different conditions of the production processes based on visual information.

3 OVERVIEW

As shown in Fig. 2, our proposed system is composed of three modules: the bimanual sewing module (Kuka Robot A, B, Needle Driver A, B), the mandrel module (Robot C, Mandrel, and Fabric), and the vision module (stereo camera). This setup separates the sewing task into two parts: bimanual sewing and handling the fabric and the stent. The bimanual sewing motion is learnt by observing human demonstrations while the motion of mandrel is computed according to the personalized design. The three robots are synchronized by visual servoing (Section 3.3).

The role of each module is listed as below:

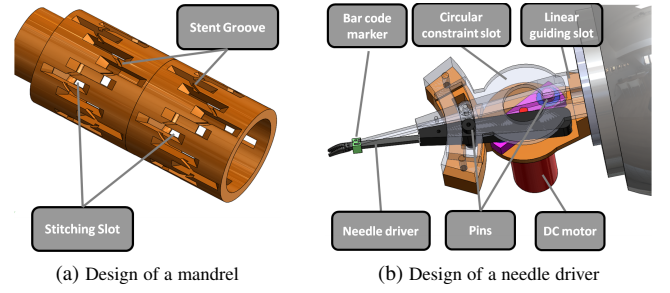


Fig. 3: (a) The mandrel. The stitching slots are for needle to sew and the stent grooves are for fixing the stents. (b) The motorised needle driver. It is designed to be attached to the Kuka robot and has a DC motor that opens and closes the needle driver.

1) Mandrel module

- a) Personalized trajectory planning
- b) Handling stent and fabric

2) Bimanual sewing module

- a) Learning and reproducing human hand sewing
- b) Adaptation

3) Vision module

- a) Watching and recording the user demonstration of bimanual sewing;
- b) Tracking the motion of the needle drivers and visual servoing the robots;
- c) Detecting the needle pose and adapting the robot motion accordingly.

3.1 Mandrel Module

The key to the personalization of the stent graft is the 3D printed patient specific mandrel. A mandrel is a hollow cylinder to support the fabric and the stents. Fig. 4 shows a basic mandrel. The shape of the mandrel needs to be customized together with the fabric to fit to each patients anatomy. This mandrel plays two important roles during the manufacturing process: 1) tightly bind the stent and the fabric together and minimize fabric deformation and 2) enable the robots to sew according to the patient specific design. Before sewing, the mandrel with stent and fabric tube is affixed to a robot via a 3D printed adaptor. This adaptor is an octagonal prism with a vision-based marker on each face. The pose of the mandrel is computed by detecting the pose of the markers as detailed in Section 3.3.

The mandrel movement controlled by Robot C is computed according to the mandrel design. After completion of each stitch, the mandrel is moved automatically to align the next sewing slot with the Robot A and Bs trained piercing position (Section 3.2). The location of each sewing slot can be obtained from the CAD file of the mandrel and therefore the trajectory of Robot C can be programmed beforehand to cooperate with the bimanual sewing module. In this way, the sewing process can adapt to any type of personalized stent graft designs.

3.2 Bimanual Sewing Module

This section presents the approach we took to transfer human hand sewing skill to robots. Hand sewing is a time consuming job

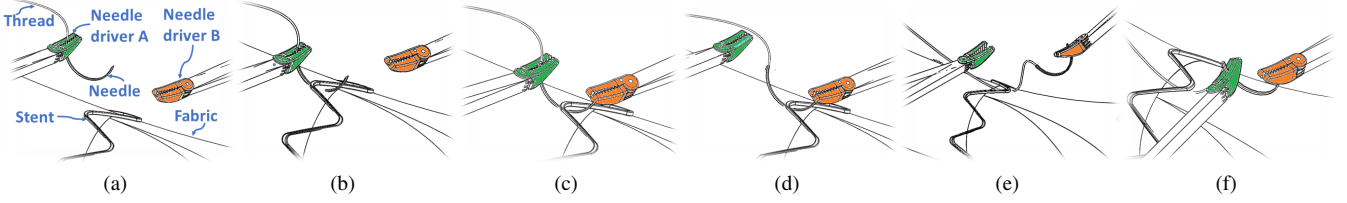


Fig. 4: The key steps involved in one stitch cycle (a-f), of which at the end the needle is passed back to Needle Driver A for the next cycle.

requiring fine manipulation skills. Although there exists a large variety of specialized sewing machines, many hand-sewing tasks are difficult to automate, as they involve complicated interaction between multiple objects, e.g. thread, fabric, needle and stent. To this end, we have adopted a learning by human demonstration approach to simplify the task. The hand motion of sewing the stent graft was first demonstrated by a user, and then segmented to multiple motion primitives, each encoded with a statistical model. These models were then implemented allow the robot to reproduce the same stitches. The demonstrations were observed by the vision system and the learned reference trajectory was later reproduced under vision guidance and servoing.

Two robot arms (Kuka robot A and B) mounted with two end effectors (needle driver A and B)¹ and a curved needle are used for bimanual sewing. This is a typical bimanual manipulation system and the target object is the needle. In subsequent sections, we refer to the needle as the *object*, and the needle drivers as the *tool*. Here we use an object centric approach: the human skill is represented by the motion of the tools and the objects. During demonstration, the user controls the tools to manipulate the object. The motion of the tools and object, rather than the human hand, is recorded and learned. In task reproduction, the robots use the same tools to manipulate the same object. In this way, the human manipulation skills can be easily transferred to robots, without the need of mapping the human motion to the robots.

3.2.1 Data Acquisition

To demonstrate bimanual sewing for the robots to learn, the user held two needle drivers with hands to manipulate the needle. Two bar-code markers for visual tracking were mounted on the needle drivers. The vision module was mounted on top of the workspace to record the 6 d.o.f poses of the needle drivers. The sewing was performed on a pre-installed mandrel.

Sewing is a repetitive task and Fig. 4 shows the main steps for a single stitch cycle. A surgical 1/2 curved needle was used for sewing: its sharp end is referred to as the *needle tip* and its blunt end is referred to as the *needle end*. The two needle drivers are motorized from two surgical needle drivers, which can provide a strong grip to the needle. During sewing, the needle was held by the two needle drivers alternately. Its trajectory was computed according to the pose of the needle drivers and their relative orientation. The estimation of the needle pose is presented in Section 3.3.2. When a needle driver was holding the needle, both the needle and the needle driver trajectories were recorded, in the frame of the mandrel; when the needle driver was not holding the needle, only its own trajectory was recorded, in the frame of the needle. It is worth noting that needle pose estimation was performed at the beginning of each stitching cycle. The user can

1. These are surgical needle drivers that are specially designed to grip the needle firmly. They are motorized to let the robots to open and close.

TABLE 1: Motion primitives of stitching

Motion Primitives	Steps in Fig. 3	Needle Driver A status	Needle Driver B status	Needle status
1.	a, b	Closed	Open	With A
2.	c	Closed	Closed	With A
3.	d,e	Open	Closed	With B
4.	f	Closed	Closed	With B
5.	a	Closed	Open	With A

demonstrate multiple times to the system to generate the training data.

3.2.2 Task Learning

After simple low-pass filtering of the raw data, each demonstration was segmented as motion primitives according to the needle drivers' open and closed status and their attachment to the needle. These motion primitives are listed in Table 1. Dynamic Time Warping was then applied [16] to each segment to temporally align all the trials.

Each aligned segment was encoded by a 7D Gaussian Mixture Model (GMM) Ω and formed a motion primitive [17], [18]. It encoded the time stamp t and the 6 d.o.f pose $h = \{x, y, z, \alpha, \beta, \theta\}$. The probability of a given point t, h belongs to Ω is computed as the sum of the weighted probability of the point belonging to each Gaussian component Ω_m :

$$p(t, h | \Omega) = \sum_{m=1}^M \pi_m p_m(t, h | \mu_m, \Sigma_m) \quad (1)$$

where μ_m , and Σ_m , π_m , p_m are the mean, and covariance of the m -th Gaussian component, prior, the corresponding conditional probability density, respectively. More specifically, the mean μ_m and the covariance Σ_m are defined as:

$$\mu_m = \begin{pmatrix} \mu_{t,m} \\ \mu_{h,m} \end{pmatrix} \quad \Sigma_m = \begin{pmatrix} \Sigma_{tt,m} & \Sigma_{th,m} \\ \Sigma_{ht,m} & \Sigma_{hh,m} \end{pmatrix} \quad (2)$$

To determine the number of Gaussian components M , a five-fold cross validation was used.

The reference trajectory of each motion primitive was retrieved via GMR by querying the mean $\hat{\mu}_h$ and the covariance $\hat{\Sigma}_{hh}$ of the pose at each time step $\hat{t}$:

$$\hat{\mu}_h = \sum_{n=1}^N \beta_n(\hat{t}) \hat{\mu}_{h,n} \quad \hat{\Sigma}_{hh} = \sum_{n=1}^N \beta_n(\hat{t})^2 \hat{\Sigma}_{hh,n} \quad (3)$$

where

$$\hat{\mu}_{h,n} = \mu_{h,n} + \Sigma_{th,n}(\Sigma_{tt,n})^{-1}(\hat{t} - \mu_{t,n}) \quad (4)$$

$$\hat{\Sigma}_{hh,n} = \Sigma_{hh,n} - \Sigma_{ht,n}(\Sigma_{tt,n})^{-1}\Sigma_{th,n} \quad (5)$$

and

$$\beta_n(\hat{i}) = \frac{\pi_n P(\hat{i}|\mu_{t,n}, \Sigma_{tt,n})}{\sum_{n=1}^N \pi_n P(\hat{i}|\mu_{t,n}, \Sigma_{tt,n})} \quad (6)$$

3.2.3 Trajectory Optimisation for Task Contexts

The learned reference trajectory needs to be further optimized to maximize the task performance in terms of both accuracy and speed. We achieved this by varying the speed of the task reproduction in different task contexts. Generally, a manipulation task has two task contexts: *end point driven* and *contact driven*. For the former, the robot is required to reach to an end point with no constraints (unless there are obstacles) on the path along which it travels, whereas for the latter, the robot contacts the environment and has to follow a particular trajectory constrained by the contact surface.

In the bimanual sewing task, the approaching and exiting motion of the needle to the fabric is end-point driven, while the piercing in and out motion belongs to the contact driven context. To ensure stitch quality, the needle piercing in and out motion must follow the reference trajectory accurately. Hence in this context, the robot is slowed down to allow it to follow the reference trajectory carefully. For end-point driven motion, however, the robot does not need to follow the exact trajectory, as long as it reaches to the final destination.

To identify the task context, the variance between different demonstrations in each motion primitive was analyzed. As shown in Fig. 8, the variance of the demonstrations varies across the task. Those parts with large variance were identified as end point driven, while those with small variance were identified as contact driven.

According to the bimanual sewing task requirement, we chose the correlation of the variance and the ratio to the demonstration speed r as:

$$r = \begin{cases} 0.5, & \text{var}_t > 0.01 \text{ or } \text{var}_r > 15 \\ 1.5 & \text{var}_t \in [0.005 \ 0.01] \text{ or } \\ & \text{var}_r \in [5 \ 15] \\ 3 & \text{var}_t < 0.005 \text{ or } \text{var}_r < 5 \end{cases}$$

where var_t and var_r are the variance of the translation in meter and the rotation in degree, respectively.

3.3 Vision Module

3.3.1 Detection and Tracking for Continuous Tool Pose Estimation

Vision-based tool pose estimation is important for robotic automation, as it can effectively correct for robot movement and calibration errors. Fig. 3 shows the motorized needle driver designed for the proposed system. In this work, we have applied a visual tracking and pose estimation scheme similar to [19]. Bar-code markers with known geometrical characteristics were attached on each tool. A pentagonal adapter was used to ensure that the marker can be observed by the stereo cameras during manipulation (Fig. 5). To allow for consistent computation of tool rotation, a different pattern was put on each face of the adapter. For every image captured by the cameras, we calculated the poses of visually available markers and then transformed them to obtain the pose of the needle driver. A similar marker design was applied to the mandrel for pose estimation.

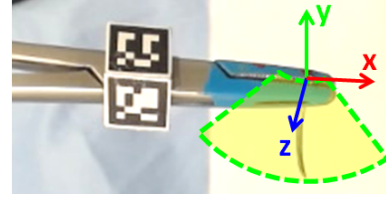


Fig. 5: A 2D illustration of the needle search space (yellow area). This search space is 4D and is restricted to $\pm 5 \text{ mm}$ for the x translation, $\pm 10 \text{ degree}$ along x, $\pm 60 \text{ degree}$ along y, $\pm 30 \text{ degree}$ along z.

Our pose estimation approach is based on consistent detection and tracking of the fiducial markers. We used the marker detection algorithm in ArUco [20], combined with an optical flow based tracker in [21]. It is worth mentioning at this point the forward-backward error identification component that we included for tracking. We used the location of a marker in the previous frame to initialize a set of corner points. These points $\{q_i\}_{i=1}^n$ (belong to the marker) were tracked “forward” from the previous to current frame, to obtain their estimated current locations $\{q_i^+\}_{i=1}^n$. In addition, “backward” tracking was also performed from the current to the previous frame, to obtain $\{q_i^-\}_{i=1}^n$. The assumption used here is that if these points have been tracked accurately from the previous to the current frame, the backward tracking would return to the original locations of these points. With this, we used the Euclidean measure to determine if a point estimate is valid, and we compared the measure with a threshold τ (defined as 1px). All the accepted points are treated as inliers, which are then used to estimate the 6 d.o.f pose of the marker using perspective-n-points [22]. Hence, our pose estimation approach has the advantage of continuous pose estimation by combining visual detection and tracking, which was applied to every marker on the adapter.

3.3.2 Needle Detection

After being handed over twice in one stitching cycle, i.e., from Needle Driver A to B and then back to A, the needle may deviate from its initial pose relative to the Needle Driver A. Although the change for each cycle may be small, it can accumulate to a large deviation from the initial needle pose, and cause task failure. Therefore, the robot motion needs to change adaptively according to the needle pose, to move the needle along its learned reference trajectory. To this end, the pose is estimated by performing a constrained 2D/3D rigid registration using features calculated in the image and a sparse representation of the 3D model of the needle, i.e., a set of 3D points along the needle shaft.

This can be represented as a constrained 2D/3D rigid registration problem. For this purpose, the transformation that describes the pose of the needle is applied to its 3D model. The resulting 3D points are then projected into the image using the cameras parameters². Restricted by the jaw of the needle driver, the pose of the needle was represented in 4D: a translational movement along the jaw and the 3D rotation. For each plausible needle pose, i.e., possible combinations of the 4 d.o.f parameters, the sum of the feature strength for the projected 3D model points is calculated (Fig. 5). Finally, the pose that is characterized by the highest overall feature score is regarded as the pose of the needle. In fact, the higher the feature score, the higher the likelihood that the projection of the 3D model of the needle overlaps with its

2. The cameras parameters are estimated during an offline calibration phase.

image representation. Due to the elongated structure of the needle, an image feature that has a strong response to lines and curvilinear objects [23] was used. How the robot adapts its motion to the needle pose is explained in the next section.

3.3.3 Visual Servoing

A close loop vision-based feedback system was deployed to guide the robot motions. In a multi-robot system, it is important to coordinate all the robots to work under the same frame of reference with the same pace. Calibration of multiple robots is time-consuming, especially for delicate tasks such as sewing or surgical tasks in order to achieve an adequate precision. To this end, we applied a 3D visual servoing technique to ease the requirement of the accuracy of this calibration. With online vision feedback, the error of the robot reproducing the reference trajectory is independent of the calibration and the robot kinematic precision [11].

In our sewing system, multiple reference frames are involved: camera (c), mandrel (m), stitching slots (s), needle (n), needle driver (d), robot base (r) and the robot end effector (ee). Here we denote yH_x as the homogeneous matrix of the pose of an object x in the frame of an object y.

The aim of the visual servoing is to move the needle or the needle drivers to follow the learnt trajectory in the frame of the stitching slots. Prior to the task demonstration, the mandrel was registered to the end effector frame of Robot C, and each stitching slot was registered to the mandrel (mH_s). Each personalized mandrel requires one registration. The poses of the needle drivers (A, B) in the robots (A,B) end effector frame were also computed. All robots were registered to the frame of the camera (cH_r). This was achieved by hand-eye calibration³.

For both the mandrel and the bimanual module, we adopted the “look-and-move” servoing method to control the robot movements. In this method, the target is to minimize the error between the current pose and the target pose of the observable objects, i.e. the markers on the mandrel and on the needle drivers. The location of the stitching slot used for demonstration (s_0) in the camera frame was firstly registered to the camera by:

$${}^c x_{s_0} = {}^c x_m \cdot {}^m H_{s_0} \quad (7)$$

Hence, for the mandrel to deliver the i -th stitching slot to the same location, the error in pose was computed as:

$${}^m x_{m_i} = ({}^c x_m)^{-1} \cdot {}^c x_{s_0} \cdot ({}^m H_{s_i})^{-1} \quad (8)$$

This then can be transformed to the error of the Robot C end effector by the ${}^{ee}H_m$ and hence to generate commands to move the mandrel to the target pose. Note different mandrels will have different values of ${}^m H_{s_i}$.

The same principle was applied to control the bimanual sewing module. Taking the Motion Primitive 1 as an example, the aim is to move the needle towards the correct stitching slot and pierce the fabric. Hence the reference trajectory was represented as a series of needle pose in the frame of the stitching slot (${}^s x_n$). The needle pose was transferred to the needle driver pose by:

$${}^s x_d = {}^s x_n \cdot ({}^d H_n)^{-1} \quad (9)$$

TABLE 2: Qualitative results of needle puncture task. Trial 1, 3 and 4 have no observable errors (denoted by -).

Needle pose	θ_x (degree)	θ_y (degree)	θ_z (degree)	X (mm)	Error (mm)
1	-1.00	0	8.51	-1	-
2	0.41	-9.39	-0.12	0	1.63
3	0.12	-0.99	1.50	-2	-
4	1.17	6.49	10.0	1	-
5	-2.88	21.00	7.43	-2	0.5
6	-2.00	6.00	13.53	-3	0.8

where ${}^d H_n$ is the needle and needle driver relative pose detected over the task as explained in Section 3.3.2. With different needle poses, the robot will adapt its trajectory to ensure the ${}^s x_n$ remains the same, i.e. to produce the same stitch.

Similar to the mandrel module, the error between the current needle driver pose (d) and the desired needle driver pose (d^*) was computed as:

$${}^d x_{d^*} = ({}^c x_d)^{-1} \cdot {}^c x_{s_i} \cdot {}^{s_0} x_{d^*} \quad (10)$$

This, again, can be converted to the error of the robot end effector and to control the robot to move to the desired location.

To increase the stability of visual servoing and to compensate for the latency of the cameras, a Double Rate Kalman Filter was applied to the estimation result of the mandrel and needle driver poses, as explained in our previous work [24].

4 EXPERIMENTS AND RESULTS

Two tasks were implemented to evaluate the performance (accuracy and the robustness) of the proposed system: 1) a needle puncture task and 2) the autonomous sewing of personalized stent grafts. The details of the experiments and results are described here.

4.1 Needle Puncture Task

The needle detection and the visual servoing algorithm were evaluated with a puncture task: teaching the robot to puncture a fixed point on a fabric with a needle. This motion was demonstrated by a user using a needle driver to hold and move the needle. At the beginning of the motion, the needle was placed away from the fabric and the needle pose was estimated by the algorithm presented in Section 3.3.2. The user moved the needle to approach the fabric and finally punctured the fabric at a fixed point. The motion trajectory of the needle driver and the needle were recorded by the vision system with 640×480-pixel videos. The robot then learned to reproduce the trajectory and puncture the fabric at the same location. The locations of the puncture points in different trials were recorded. These demonstrations were performed using a 1/2 circular needle with 8mm diameter, of which the model has 10 evenly distributed points along the arc.

Six experiments were conducted and at each trial, the needle pose varied as shown in Fig. 6. After needle pose estimation, the robot adapted its motion trajectory to deliver the needle by visual servoing to puncture at the same point. The motion was reproduced in a third of the speed of the human demonstration. The error of each experiment was computed as the distances of the repeated puncture points with respect to the original puncture

3. From Matlab: <https://uk.mathworks.com/matlabcentral/fileexchange/22422-absolute-orientation>

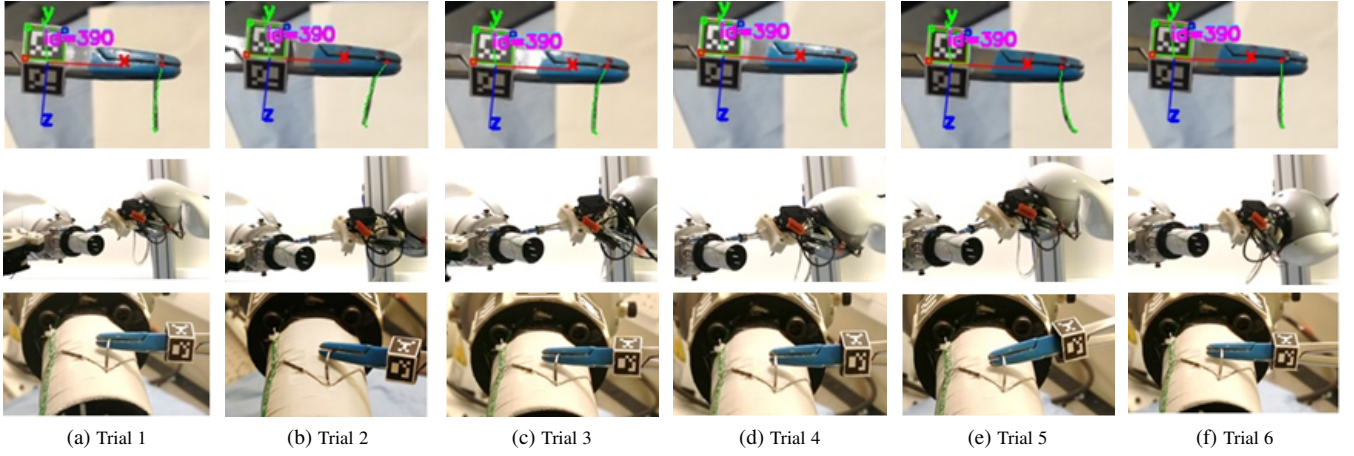


Fig. 6: Experiment results for needle puncture task with six different initial needle positions. Top row: Results of needle 3D pose detection. The detected needle pose 3D pose is projected as the green lines. The red dots mark the end of the detected needle. The pose of the needle driver is detected by the marker, denoted by the frame. Middle row: The robot adaptation of the needle poses during the puncture task execution. Bottom row: At the end of the task, the needle punctured the fabric.

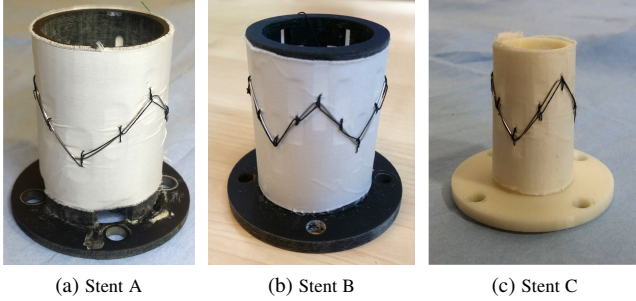


Fig. 7: Stents in different designs. Outer diameters are: 4.4cm, 4cm, 3cm.

point. This error reflects the overall accuracy of the entire vision module, including the needle detection algorithm, tool tracking, and the visual servoing method.

As shown in Table 2, in half of the trials the robot punctured at the same point as demonstrated. The average error across the six trials was 0.48 mm . Trial 2 resulted in a larger error (1.63 mm) as during the motion, the robot arm approached its joint limits and hence and only reach the adjacent points. This result shows that the accuracy of the vision module allows for high precision sewing for the stent grafts.

4.2 Autonomous Sewing of Personalized Stent Grafts

To evaluate the performance of the proposed multi-robot sewing system, three experiments were conducted to sew different size stents to fabric tubes. These stents were different in their shape and diameters (Fig. 7). Stent A and Stent C were hand made by medical stainless steel wire while Stent B was cut from a sample stent graft. The fabric was Dacron graft and the sizes were chosen from the personalized sizes available from current stent graft manufacturers. According to the design of these stents, their corresponding mandrels were 3D printed. On each mandrel, $10 \times 2 \text{ mm}$ stitching slots were created. They are located at the peaks of the stents and at the middle point between the peaks. Before

sewing, the fabric tube and the stent were manually loaded onto the mandrel and the whole device was mounted on Robot C.

The robotic sewing system is shown in Fig. 2. All three 7 d.o.f robots were registered to the vision module mounted on the top of the working space by hand eye calibration. The system was demonstrated by five times of the bimanual sewing on the same slot of Stent A by the user. The average demonstrated stitch size was 4.10 mm . Before each stitch, the needle pose was detected such that the needle trajectory can be computed by the needle driver trajectory.

The human demonstration motion primitives are shown in Fig. 8. Note we have omitted in the figure the trajectories of the Needle Driver A in Primitive 2,3 and the Needle Driver B in Primitive 1,4,5 as they are nearly static. As presented at the bottom row, the variance of each motion primitive varies across different stages. For example, in Primitive 1 the motion variance of Needle Driver A is large at the beginning, i.e., approaching the fabric, and rapidly reduces to a small value, i.e. piercing in the needle. This suggests that piercing motions were highly similar among all demonstrations and thus required to be followed precisely. For the same reason, in Primitive 2 and 3 the variance of the Needle Driver B motion is large when approaching or leaving the fabric, and small when piercing out the needle. Primitive 4 and 5 are shown in the needle frame. According to the variance, the Needle Driver A gripped at the same place of the needle at every demonstration. To conclude, for the interactive parts of the task, i.e. needle piercing in/out of the fabric and needle handing over, the variance of the motion is small and hence we slow down the robot for these parts to ensure precision. For the other parts we increase the velocity of the robot to maintain the speed of sewing.

The learned reference trajectories were registered to the mandrel's frame via its stitching slots. As mentioned in Section 3.3, the mandrel's pose was detected according to the fixed markers on the adapter. During robot sewing, Robot C would rotate and translate the mandrel to the desired location to allow for ease of access to each stitching slot, with its pose detected by the camera. The motion of Robot C was computed automatically according to the stitching slot locations. The planning was done offline for each stent.

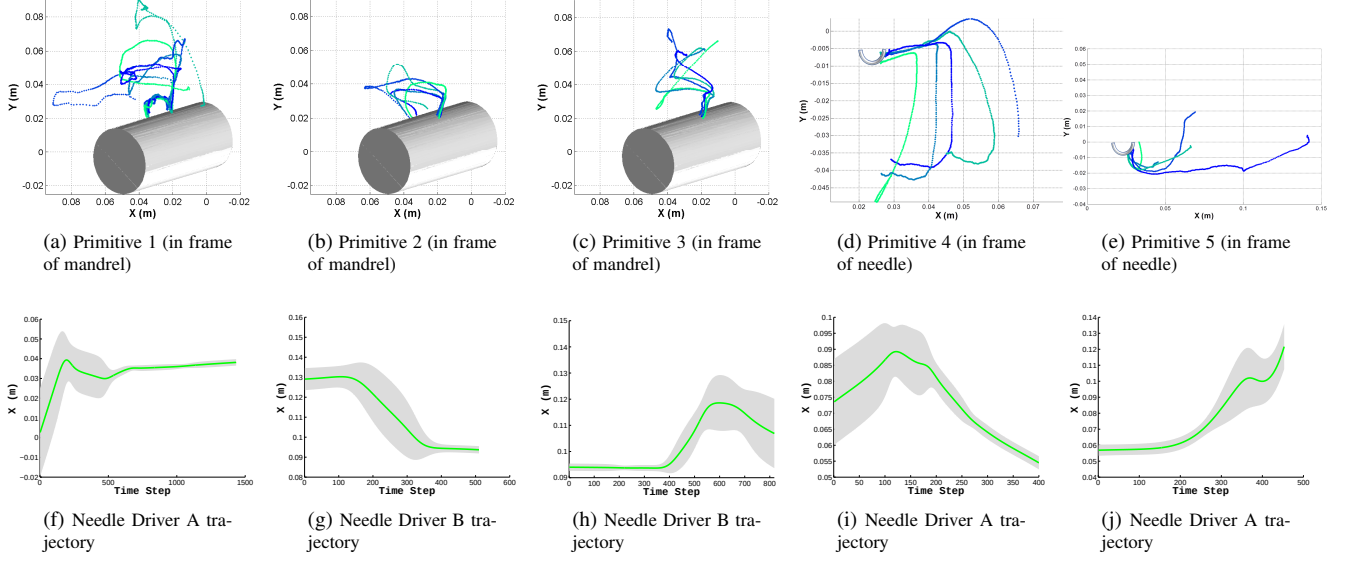


Fig. 8: The needle drivers trajectories from human demonstrations and the learn reference trajectories of each motion primitive. (a)-(e): Five human demonstrations of bimanual sewing. Different colors represent different trials. The grey cylinder in (a)(b)(c) represents the mandrel. The grey arc in (d)(e) represents the needle. (f)-(j): 2D projection of the motion primitives on the x-axis. Green lines represent the reference trajectories, and the grey area represent the corresponding variances.

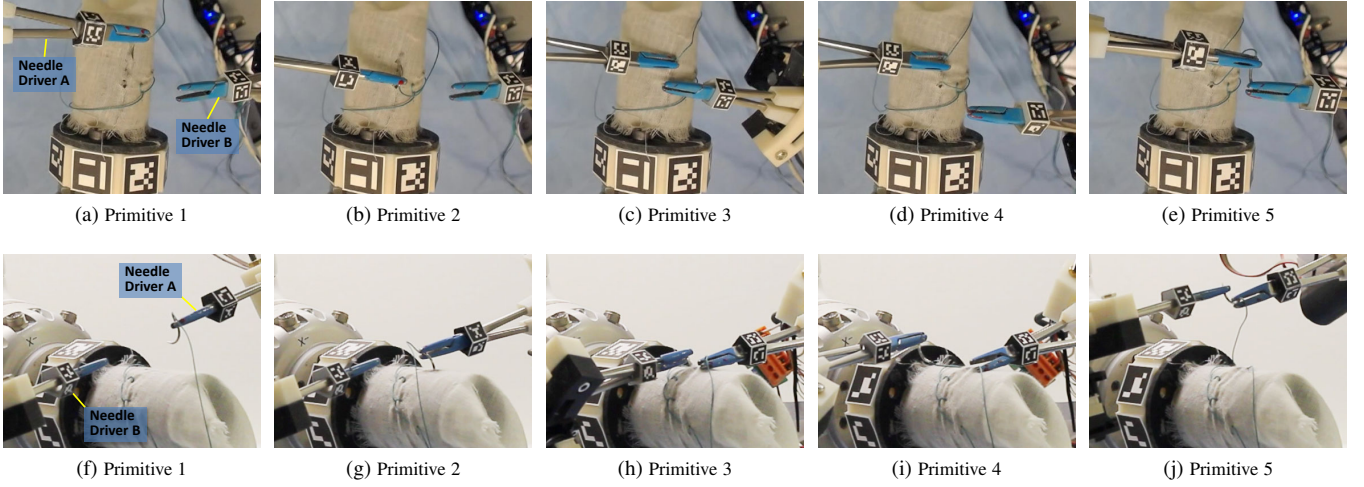


Fig. 9: Key frames of bimanual sewing in each motion primitive. (a)-(e) The view from the top camera, used for visual servoing. (f)-(j) The corresponding views from the side.

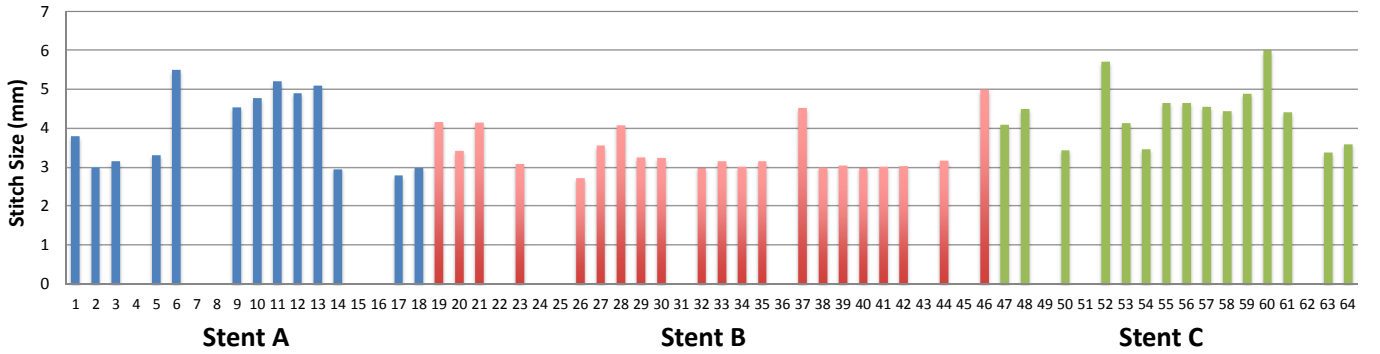


Fig. 10: Experiment results of sewing stent A (blue:1-18), B (red: 19-46) and C (green: 47-64). In total 64 trials have been taken and the success rate is 77% with mean stitch size 3.93 mm. Trials with no stitch size denote failed stitches.

Before the robot performing a stitch, the reference trajectory was adapted according to the detected needle pose. After finishing a stitch, the robot was programmed manually to tighten the stitch. This pulling motion was adapted according to the estimation of the remaining length of the thread. When a stitch failed, the needle was placed back to the initial pose and the system was restarted.

For these three stents, 64 stitches were made in total with an overall success rate 77% and average stitch size of 3.93 mm. The size of each stitch is reported in the Fig. 10. There are four possible causes of a failed stitch: 1) handing over needle failed (trials 4, 7, 8, 36, 43, 45); 2) stitch missed the stent (15, 16, 31, 49, 51); 3) needle touched stent (24, 25); 4) needle entangled with the thread (22, 52). The first three causes were mainly due to errors of the needle detection and visual servoing. Improved resolution of the video of the scene can improve the accuracy. In this work, we do not control the shape of the thread and hence it also caused several failures.

5 DISCUSSION AND CONCLUSION

In this paper, we have proposed a robot platform for manufacturing personalized stent grafts. We have explored a practical solution for mass production of personalized products at system level. We have also developed novel vision and trajectory planning approaches to let robots to imitate human hand sewing. Experiments were conducted to evaluate the entire system in terms of its accuracy and robustness for sewing personalized stents. It is worth noting that multiple throw hand sewing has been a challenging task to automate [25]. It involves complex motion planning, multi-robot cooperation, handing over small object, i.e. a needle, and continuous monitoring of the process. The proposed system is able to achieve 77% of overall success. The targeted stitch size was 4.10 mm and the system achieves an average stitch size 3.93 mm.

The proposed multi-robot system includes a mandrel module to control the personalization of the product, a bimanual sewing module to learn and perform the hand stitching, and a vision module to guide the entire system and ensure the accuracy achieved. For bimanual sewing, our vision-based programming-by-demonstration approach enables not only users to demonstrate bimanual tasks with tools in their own hands and but also the robot to execute the task with varying speed according to the task context. By using the same tools and markers for task demonstration and reproduction, user demonstrated motion skills can be transferred to robots seamlessly. Experiments showed that this system presents sub-millimeter accuracy, and thus it practical value.

Furthermore, the modularized design of the system increases the flexibility of the system and reduces the complexity of the task. For sewing different stent grafts, only the mandrel is required to be changed. This makes the system to be easily extended to other manufacturing tasks.

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