

VISUAL LOCALIZATION OF TISSUE CUT, SUTURE NEEDLE AND SUTURE THREAD FOR AUTONOMOUS SUTURING IN MULTI-VIEW CAMERA STREAMS

A Thesis

by

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Submitted to the
Graduate School of Sciences and Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in the
Department of Computer Science

Özyeğin University
February 2024

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To my family

ABSTRACT

Autonomous suturing systems could potentially replace the surgeon in suturing and benefit both patient and surgeon. Automating the suturing process involves many complex challenges and this paper proposes a comprehensive solution to the localization problems. In this context, localization problems refer to the challenges involved in the visual tracking of suture needle, suture thread, and tissue, which are fundamental processes for autonomous suturing that must be robust, precise, and computationally affordable. Surgical instruments' reflective, superfine, or non-rigid structures make their localization a complex problem. The contribution of this study is that it provides a combined algorithm for suture needle and thread detection, an algorithm for tissue cut detection. The overall localization approach proposed here defines the suture needle and its thread with fewer parameters, enabling a more precise and less computationally intensive localization. For the testing of the proposed approach, an experimental setup featuring two 7-DOF robots equipped with surgical instruments and two fully calibrated cameras were utilized. The localization experiments were done using realistic artificial (silicone) tissues and threaded surgical needles. The results of the experiments validated that the proposed method meets the requirements for performing automated robotic sutures.

ÖZETÇE

Otonom suture sistemleri monoton görevlerde cerrahın iş yükünü azaltarak hem hastaya hem de cerraha fayda sağlayabilir. Suture işleminin otomatikleştirilmesi birçok karmaşık zorluğu içerir ve bu makale, görsel tespit sorunlarına kapsamlı bir çözüm önermektedir. Bu bağlamda, görsel tespit sorunları, gürbüz, kesin ve hızlı olması gereken otonom dikiş için temel süreçler olan suture iğnesinin, suture ipliğinin ve dokusunun görsel olarak izlenmesiyle ilgili zorlukları ifade eder. Cerrahi aletlerin yansıtıcı, çok ince veya esnek yapıları, lokalizasyonlarını karmaşık bir problem haline getirmektedir. Bu çalışmada, doku kesiğini otomatik tespit eden bir algoritma, suture iğnesini ve ipliğini ise bu iki ekipmanın fiziksel bağlantı noktasını kullanarak tespit eden bir algoritma sunulmuştur. Çalışmanın genel tespit stratejisi, suture iğnesini ve ipliğini daha az parametreyle tanımlayarak, daha kesin ve daha az hesaplama maliyetine sahip bir tespit sistemi uygulamasına olanak sağlar. Tespit sistemlerinin test edilmesi için, cerrahi aletlerle donatılmış iki adet 7-DOF robotu ve iki adet tamamen kalibre edilmiş kameradan oluşan bir deney düzeneği kullanılmıştır. Tespit deneyleri gerçekçi yapay (silikon) dokular ve cerrahi suture cerrahi iğneleri kullanılarak yapılmıştır. Deney sonuçları, önerilen sistemin otomatik robotik suture atılmasına yönelik gereksinimleri karşıladığını doğrulamıştır.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Asst. Prof. Özkan Bebek, with whom we worked together day and night, sometimes for weeks, during this challenging project. I have learned a lot from him about academic discipline and writing articles. I am very grateful to Prof. Dr. Erhan Öztıp for his valuable insights, motivations, and critiques that always bring me further steps. I learned so much along the way; none of it would have been possible without my advisors. I would also like to thank the committee members, Assoc. Prof. Emre Uğur, Asst. Prof. Sedat Özer and Prof. Dr Hasan Fehmi Ateş, who devoted their valuable time to evaluate my thesis.

I am grateful to Begüm Sunal, Oğulcan Çingiler, and Negin Armirshizad for their collaboration on the project, as well as to Ahmet Burhan Kara and Mustafa Derman for their assistance in 3D part design and printing. I also thank Kutay Selçuk, Ata Çorumluoğlu, and Özkan Bebek for generously sharing their cameras with me. My deepest gratitude goes to my family for their unwavering material and spiritual support, and I thank them for their constant trust and encouragement.

Finally, I would like to express my deep gratitude to Hazal Bayzin, who provided calm and focus during the challenging and tumultuous periods of this journey.

This research was done at Özyeğin University Robotics Laboratory and supported by the the Scientific and Technological Research Council of Turkey (TÜBİTAK), under grant number 119E036.

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CHAPTER I

INTRODUCTION

Robotic Minimally Invasive Surgery (RMIS) constantly enhances traditional surgical procedures, which offers many advantages to patients, including the reduction of infection, expedited recovery, minimal postoperative scarring, and reduced blood loss. Skilled surgeons can execute delicate and intricate procedures with remarkable precision by utilizing these advanced robotic manipulators, thus optimizing overall surgical efficacy [1]. Conversely, mediated by interfacing devices, the synergy between the robot and the practitioner induces a consequential diminution of dexterity, maneuverability, tactile strength, or visual acuity. Consequently, RMIS is prolonged [2] and exhausting for surgeons. Since there is a robotic interface between the doctor and the patient, it is possible to reduce the burden on the surgeon by automating some monotonous tasks in long-lasting operations [3].

Suturing is an example of one of those monotonous tasks that are repetitive and frequently applied in various types of surgeries. The purpose of suturing is to join two cut tissue edges together with minimal tissue damage [4]. One of the simplest ways to perform this task is to place interrupted sutures at intervals along the incision [5]. A single interrupted suture involves needle insertion, needle pull-out, and knot-tying with thread [6]. In the insertion, the suture needle tip is immersed under the tissue at a planned entry point and emerges from the planned exit point. The inserted suture needle is removed from the tissue by pulling from the tip of the needle, leaving the thread in the tissue. The incision is closed by joining two edges of the tissue in the last step by tying a tensed knot. Repeating these main stages constitutes the complete closure of an open wound.

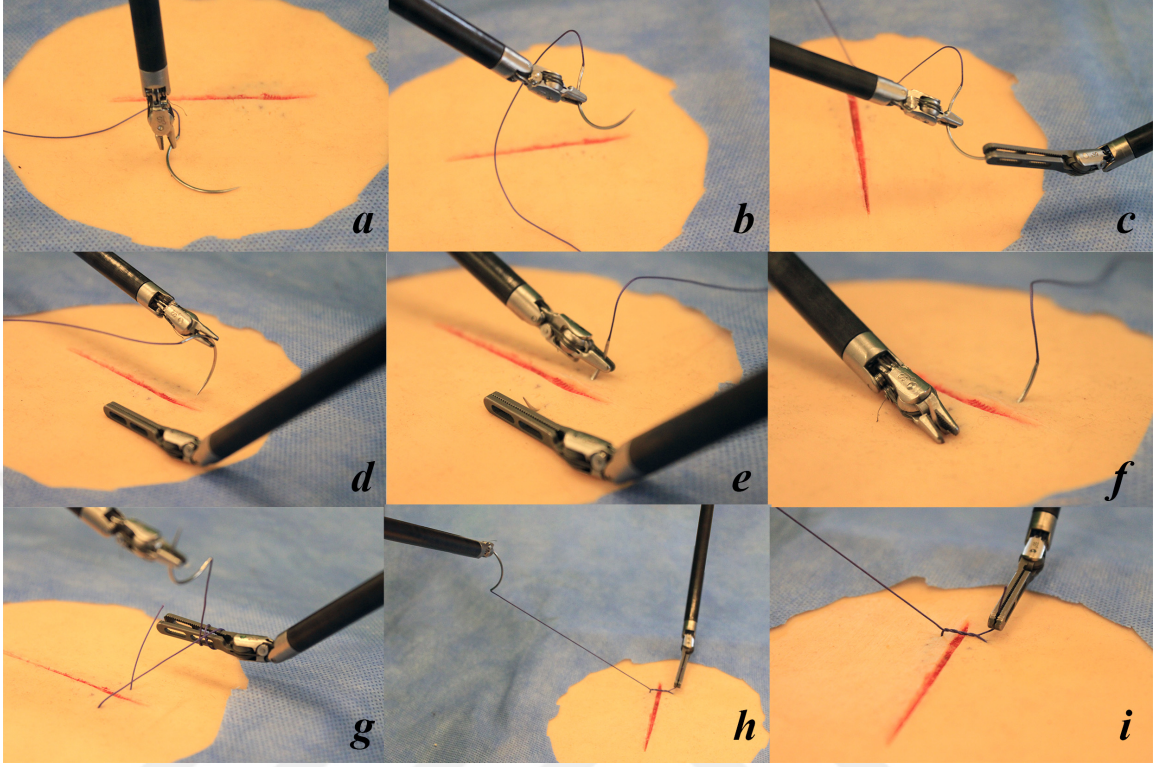


Figure 1: Steps of single interrupted suture with robotic hands

Automated suturing replaces the surgeon [7] with a comprehensive closed-loop system that capable of autonomously executing suturing stages safely and precisely. Therefore, it requires the combination of interdisciplinary synthesis of several study domains, such as robotic control [8], transfer learning of suturing primitives from surgeon to robot [9], localization of surgery instruments [10] and tissue. The real-time detection and tracking of suture needle, thread and tissue with high accuracy and precision is fundamental for successful automation. Replacing the surgeon with an autonomous system requires additional intermediary steps on top of the individual suturing stages. While these additional steps, such as picking up a needle for insertion, are straightforward for surgeons, these tasks pose a challenge for robotic systems.

Thus, to enable autonomous suturing with robots, certain modifications must be incorporated into the typically defined suturing steps. Accordingly, a suturing process with finer granularity can be given as: (i) Picking up the needle before the insertion

task (Fig. 1-1), (ii) Needle pose correction to prepare the needle for penetration into the tissue (Fig. 1-2 & 3), (iii) Holding the tip of the needle for the pull-out task (Fig. 1-6), and (iv) Knot tying (Fig. 1-7, 8 & 9)).

These stages are essential to fulfill robotic suturing. For instance, to ensure the suture needle is fully inserted into the tissue, the needle holder must grip the needle close to the thread. As the insertion task progresses, the majority of the needle becomes out of sight, and the success of the insertion relies on the initial grasping pose, which is determined by the imaging system. Failure in these individual stages would reduce the success rate.

Visual tracking becomes challenging due to the reflective surfaces and non-textured, deformable structures of the surgical instruments. These characteristics pose significant challenges for sensor-based detection and applying standard pose estimation algorithms. Furthermore, in the context of neural network applications, manual labeling them becomes markedly laborious without automatic segmentation [11,12] or a simplified design framework.

This thesis focuses on the detection and tracking of the suture needle, thread, and tissue with high accuracy and precision to enable an autonomous suturing systems. Specific emphasis was placed on these tasks: (i) initial detection of the tissue cut and the suture needle prior to suturing process. (ii) grasping the pose computation (Fig. 1-b), (iii) tracking the suture needle during insertion (Fig. 1-d & e), (iv) localizing the tip point of the suture needle before pull-out (before Fig. 1-f), (v) localizing the tip point of the suture-thread before knot-tying (Fig. 1- g).

Table 1 outlines the visual processing algorithms developed for the steps of the suturing procedure, which are briefly introduced below and detailed in the subsequent subsections.

During the suturing steps (Fig. 1 (a)-(f)) there are two features of the suture needle that are visible in the camera frame, which are the swaged end and the tip of the

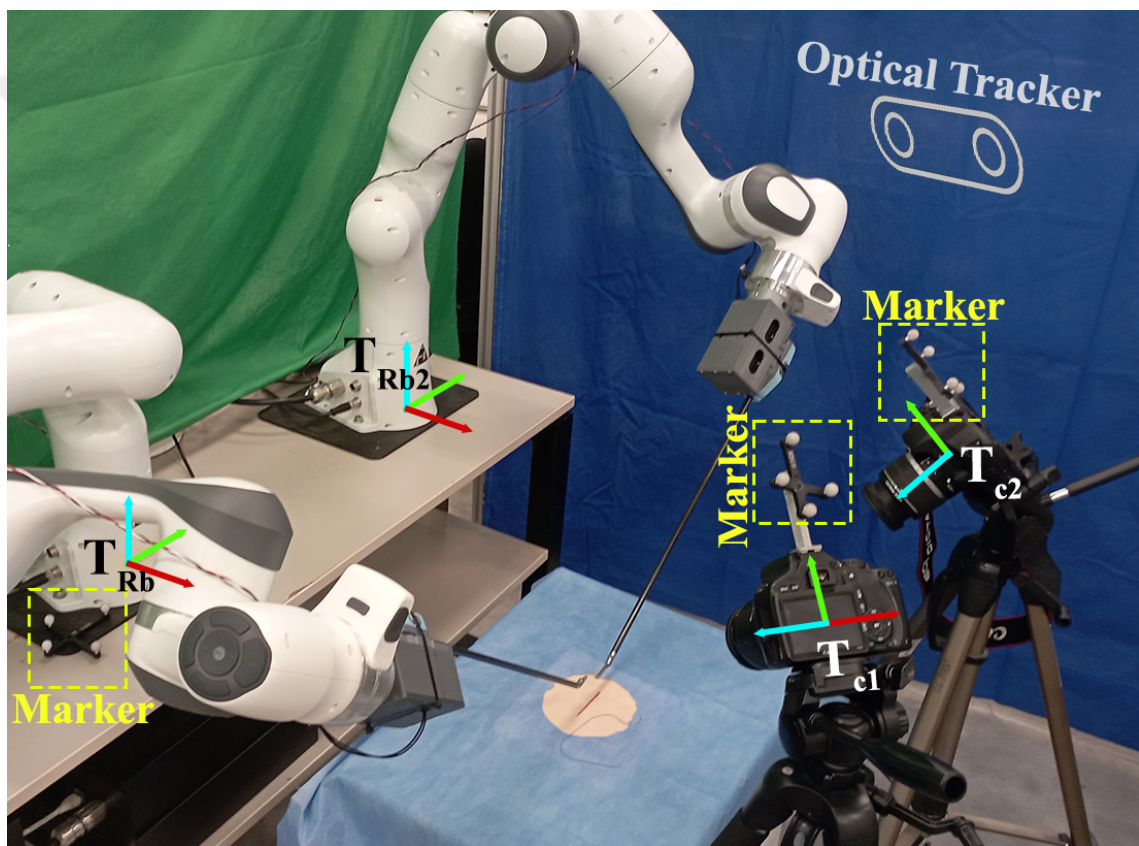


Figure 2: The experimental setup for autonomous suturing.

Table 1: The sequence of operation of localization pipelines

Suturing Steps	Tissue cut	Suture needle		Suture Thread
	Detect	Detect	Drive	Detect
a	✓			
b, c		✓		
d, e, f			✓	
g, h, i			✓	✓

needle. This has given the opportunity to base the *suture needle localization* strategy on tracking those two features with small number of parameters to reconstruct the needle. The methodology consisted of a normalized cross-correlation (NCC) process to measure the similarity of the templates, and a particle filter to fuse the needle velocity and the matched template. The *suture thread localization* associated the view of the thread to simplified node-edge graphs where nodes were discontinuous points of the thread, and edges were curvilinear segments of the thread. The node points were computed using a low-thresholded corner detection algorithm, and the edges were the result of a Breath First Search (BFS) algorithm applied on a map constructed with a HFV filter. The *tissue cut localization algorithm* consisted a U-Net neural-network and Hough line detector. For simplicity, the tissue was fixed; consequently, the detection algorithm run only once before the suturing planning.

The image acquisition system utilized was constructed with pre-calibrated two cameras. The reconstruction of the all pipelines utilized multi-view geometry for points, vectors, axes. The global reference frame for the multi-view camera geometry was assumed to be the reference frame of the first robot, given as T_{Rb} in Fig. 2.

Consequently, the tissue-cut is localized and the operation planning is autonomously generated for the autonomous suturing.

1.1 *Contributions*

This thesis proposes a comprehensive solution for designing a visual tracking system for automated suturing by reducing the complexity of the localization methods used in autonomous suturing. This work is first to provide a comprehensive visual tracking solution for achieving robotic autonomous suturing. The tissue cut detection system capable of automatic suture planning was designed. Using this localization design in the planning phase, which is the first step of the autonomous suture, automation of the suturing becomes one step further than the literature. Suture planning can be easily changed depending on given suture lengths, potentially appropriate for suturing applications in different surgery types. Additionally, the dataset used by this detection system contributed to the literature.

Suture needle localization is a system that works with a few parameters that have been contributed to the literature. This system has superior FPS performance and sufficient precision and is suitable for surgical operations. Another contribution of this localization pipeline is scanning the suture needle by its standard features for various suture needle models. Therefore, the proposed localization design can be applied to suture needle models.

An additional procedure has been proposed to facilitate visual verification and refine the suture needle insertion process. This procedure minimizes the velocity conversion error between the suture needle and the robotic manipulator.

Finally, the suture thread is detected with a robust pipeline against situations that create difficulties during visual detection, such as self-intersection and occlusion. With this pipeline, the complex and interlocking image of the suture needle on the camera can be transformed into a node-edge graph that can be easily understood and interpreted. The knot-edge chart enables the interpretation of the suture thread through the chart and the knot definition in a simple way.

1.2 Thesis Outline

The study is presented in four sections in order to explain the concepts in an orderly manner. Following the introduction, the localization algorithms of tissue cutting, suture needle, and suture thread are explained in detail in the Chapters 2, 3, 4. Each chapter describes the role of the relevant surgical equipment in autonomous suturing and the challenges and requirements of visual tracking of this equipment. The advantages and disadvantages of studies in the literature are discussed according to the defined requirements. Next, the proposed visual localization pipeline is detailed to address the gaps identified in the existing literature and fulfill the specified visual tracking requirements. Experiments were applied to test the proposed pipeline, and their results were explained. The chapters conclude by comparing the experimental results, their contribution stated, and the basis for future studies explained.

CHAPTER II

TISSUE CUT LOCALIZATION

The first step of autonomous suturing is creating a suture plan that ensures the closure of the tissue cut. The suturing plan includes the number of sutures and their insertion and exit points to be placed on the tissue surface. Since the suturing plan properties depend on the cut length and pose, the position of terminal points and the length of the tissue cut must be computed.

However, the lubricious, deformable, and irregular surface of the tissue makes sensor-based applications impracticable. During operation, the sensors may slide and fall, which causes misdetection in the surgical operation. Instead, visual localization is a robust option because the visual features of the tissue cut allow recognition based on color features and tissue edges.

Therefore, the purpose of this chapter is to deliver suture planning via visual localization of the tissue cut, which is essential for the autonomous suture.

2.1 Literature Review

There are numerous studies focused on tracking wound healing process with size estimation [13], skin & wound segmentation [14], foot ulcer tissue segmentation [15], assessing the severity [16] or measuring the depth and granulation [17] of foot ulcer. Also, cervical smear segmentation [18], colorectal cancer segmentation [19], and the wound type classification [20] are other studies. Furthermore, studies on tissue simulation during the cut process [21] and soft-tissue cutting with robotic intervention [22] are present.

There are studies in the literature on tissue/wound segmentation and detection. However, these studies focused on healing or closed wounds, not the tissues that

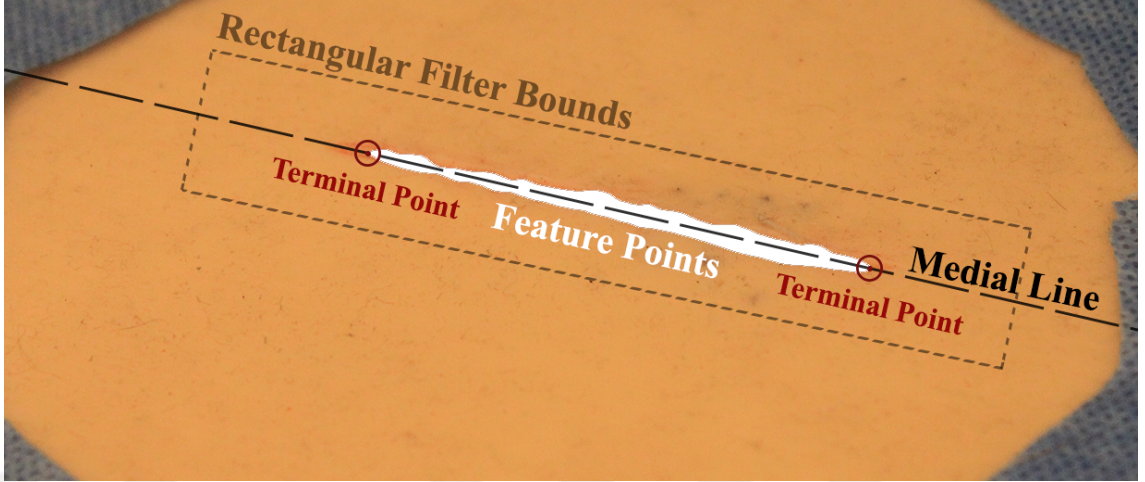


Figure 3: The segmentation of tissue cut.

needed to be sutured. These studies do not contain a data set similar to the tissue cut for suturing purposes and do not include a method for planning the suture. This study contributes to tissue cut localization for autonomous suturing applications.

2.2 Methodology

In this study, we focused on line-shaped tissue cuts. The designed tissue cut localization pipeline consists of three steps. (i) Detecting the feature points of the tissue cut with the U-Net neural network, (ii) Detecting the line passing through the middle of the tissue cut and computing the terminal points, (iii) Reconstructing the tissue and planning the suture.

2.2.1 Labelling & Training

The feature points, the points between two edges of the wound, are identified through the U-Net neural network architecture [23]. This neural network processes (800,600,3) RGB images to (800,600,1) output. The training dataset (See 4) is created from video frames taken during laboratory experiments and labeled manually with the SegmentsAI tool [24]. The architecture is trained for 3000 epochs on a custom dataset of 625 labeled images with a batch size 20. The Adam optimizer was run with binary

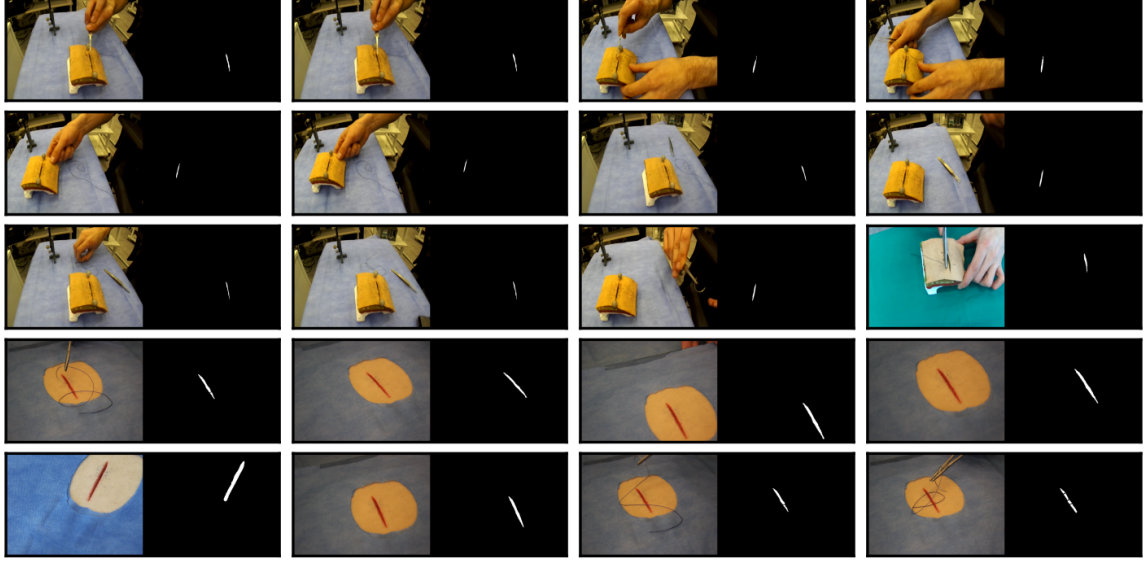


Figure 4: The samples of the data-set generated for tissue cut segmentation.

cross-entropy as the loss function and 0.001 as the learning rate parameter. The optimizer is saturated when precision is 0.801, recall is 0.628, and average IOU is 0.491. Input RGB images are normalized before training. The neural network output is the mask that amplifies the tissue-cut points with a value rescaled between 0 and 1.

2.2.2 Line Detection

The network output is thresholded with Otsu [25], then Hough Line detection [26] is applied to obtain the medial line of the tissue cut. This line is the projection of the 3D ray passing through the cut's terminal points (shown with points A and B in Fig 5).

The network output is thresholded with Otsu algorithm [25]. Since, the longest line of a linear tissue cut is passes from its terminal points (see Fig.5) the dominant corresponds to medial line of the cut. The medial line in the image the tissue cut is obtained with the Hough Line detection [26].

In the camera frame, the feature points are in a rectangular contour around the medial line. These points are masked with a rectangular box rotated around its center

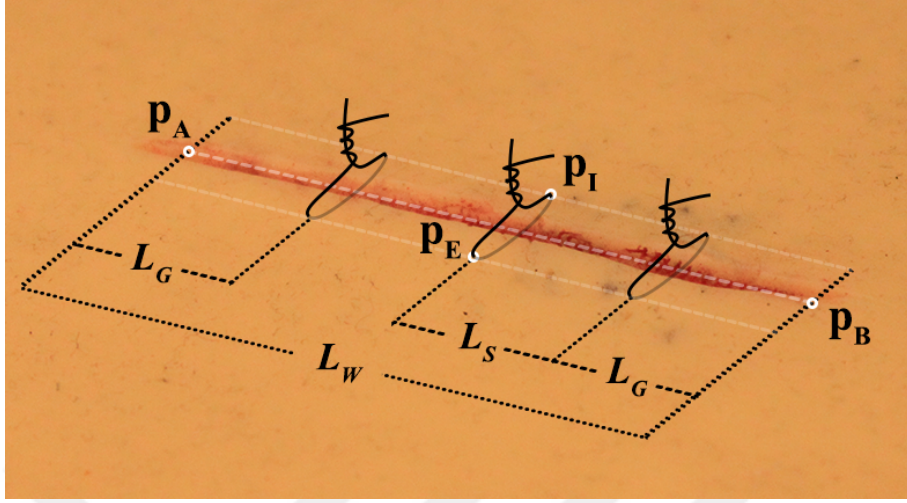


Figure 5: The general view of a suturing plan for a line shaped tissue cut.

with the angle of the medial line. This rectangular box is fixed to 50 to 200 pixels for simplification.

2.2.3 Reconstruction & Suture Planning

The terminal points on the camera frame are computed by their distance to the normal vector with equation

$$\begin{aligned} u_A &= \operatorname{argmax}(\frac{m_n x + y + n_n}{\sqrt{m_n^2 + 1}} \forall x, y \in F_p > 0) \\ u_B &= \operatorname{argmin}(\frac{m_n x + y + n_n}{\sqrt{m_n^2 + 1}} \forall x, y \in F_p > 0) \end{aligned} \quad (1)$$

where F_p are the masked points, u_A & u_B are the pixel coordinates of the terminal points, and m_n , n_n are the coefficients of the normal of the medial line in the camera frame.

The pixel coordinates of the terminal points on the first camera view u_A , u_B and u'_A , u'_B are paired and the terminal points p_A & p_B (see Fig. 5) are reconstructed using triangulation method [27].

The cut length L_W is the distance between the 3D points p_A & p_B . There are two suture gaps left between the terminal points; the number of desired sutures N_s can

be computed as eq. 2.

$$N_s = \text{floor}\left(\frac{L_W - 2L_G}{L_S}\right) \quad (2)$$

The suture spacing length L_S is an adjustable parameter for varying surgery types [28]. Adjusting the parameters L_W , L_G and L_S , the insertion and exit points of the suture can be computed with eq. (3).

$$\begin{aligned} p_e(k) &= p_A(1 - \hat{p}_d L_F) + \vec{v}_c (L_G + kL_S) \\ p_i(k) &= p_A(1 + \hat{p}_d L_F) + \vec{v}_c (L_G + kL_S) \end{aligned} \quad (3)$$

where $\vec{v}_c = p_B - p_A$, $\vec{p}_d = \vec{v}_c \times \vec{n}_t$, $\hat{p}_d = \frac{\vec{p}_d}{|\vec{p}_d|}$, and $p_e(k)$, $p_i(k)$ denotes the exit and insertion points of the k^{th} suture sample, L_F is the desired distance of the insertion point from the medial line which varies on the suture needle size, and $\vec{n}_t$ is the normal vector of the tissue surface. In the experiments, the tissue surface normal $\vec{n}_t$ was defined as the unit vector aligned along the Cartesian z -axis of the global reference frame (T_{Rb} in Fig. 2).

2.3 Experiments & Results

In order to test the precision of the designed pipeline, silicon tissue and an optical marker is fixed to a board. The tissue is weared with a light blue surgical drape to create similar view to the operation (see Fig. 6).

To determine the variance of the tissue cut localization algorithm, firstly, the board was held steady, and 544 frames in the image were collected. Then, the endpoint locations required for detection were converged using the visual localization algorithm. The localization algorithm achieved a performance of approximately 7 FPS when running on the GPU. The sum of the deviations of the estimated values of the two terminal points from the actual values was calculated as the position error. An angular error was calculated as the angle between the actual and predicted vectors defined from one endpoint to the other. Positional error (Fig.7) was calculated as 2.6 ± 1.5 mm (mean $\pm$ standard deviation) and angular error (Fig. 7) as 0.19 ± 0.15 degrees.

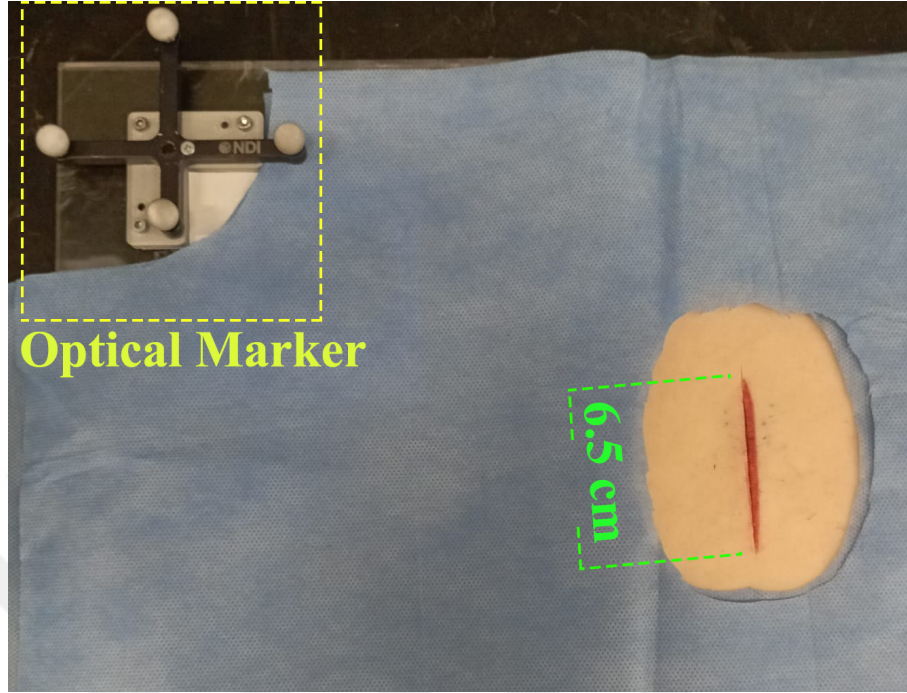


Figure 6: The board used for data acquisition in tissue-cut experiments.

The positional and angular errors in the experiments were mainly caused by the misdetection of endpoints of the tissue cut. The error may be reduced by providing geometrical constraints such as the length of the tissue cut. Also, this approach is mainly developed for fixed tissues, where average error values are appropriate in this mode. Additionally, when working with a larger suture needle, the effect of the error can be reduced.

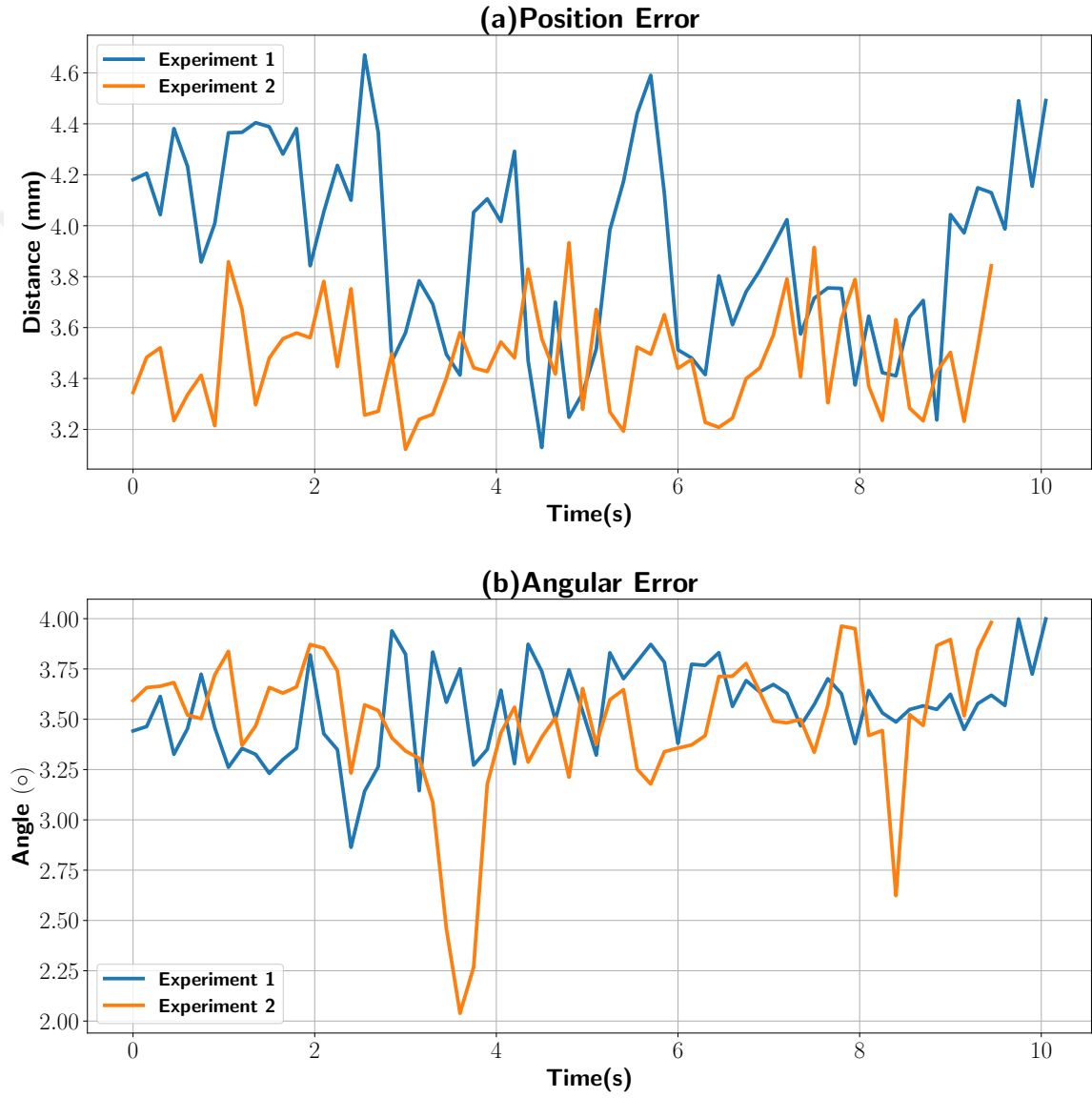


Figure 7: The position and angular error of the tissue-cut localization method.

CHAPTER III

SUTURE NEEDLE LOCALIZATION

3.1 Problem Definition

The suture needle is actively used in the pick-up, insertion, and pull-out of autonomous suture steps. Initially, the suture needle is at unknown pose, the robotic hand grasps the suture needle in the (1) pick-up phase, and the grasped needle is immersed in the tissue in the (2) insertion phase and the suture needle is thrust until its tip emerges out from the exit point of the tissue cut. In the (3) pull-out phase, the suture needle tip is grasped and pulled out from the tissue with a circular robotic hand motion. The main problem in the insertion and pull-out steps is that most of the needle is inside the tissue. Visual guidance is unavailable in this step; the suture needle tip end is driven blindly by robotic hand thrust generated on the grasping point. This movement is made using the geometric relationship between the needle and the robotic hand; therefore, the poses of the robotic hand and the needle are vital information for a successful needle tip drive. This means that the suture needle pose must be determined with high precision. Otherwise, blind driving under the tissue may result in redundant tissue damage, immersion of the suture needle, or creating a lousy or imbalanced suture, which is at best.

In addition to these challenges, the structure of the suture needle is superfine, reflective, and uniform. The suture needle occupies a small number of pixels and can disappear quickly on movement. Limited distinctive features can be tracked easily because of the uniform and non-textured surface. Therefore, the localization of the suture needle depends on processing minimal features with maximum effectiveness.

The initial unknown position of the suture needle, combined with the risk of

slippage during handling, necessitates continuous robust and precise visual monitoring of the needle during suturing for reliable performance.

3.2 Literature Review

There are numerous methods have been studied that can be applied easily, which are color algorithms [29–33] or color markers [34,35] combined with elliptic regression, circular Hough transform [36,37]. However, in surgical operations, illumination is a rapidly changing environmental factor. Color markers are unsuitable for insertion and pull-out steps because the suture needle is under the tissue. The elliptic regression is extremely sensitive to image noise. The circular Hough transform only fits the elliptical structure of the needle for a limited camera view. The elliptic Hough transform requires intense computational costs because of the hyper-parameters of the ellipse. Therefore, the color algorithms, color markers, elliptic regression, and Hough transforms are problematic for precise, robust, and real-time localization of the suture needle. As a promising study, Özgüner et al. correlated the response of the Hessian-based Frangi Vessellness Filter (HFV) of the stereo images to identify a virtually rendered suture needle characterized by four parameters [38]. They fused the velocity of the robotic hand with the data of the scanned template with a particle filter. An average translation error of 0.7 mm and orientation error of 0.89 degrees was reported with 3 FPS performance for 250 particles. In the subsequent work [39], the overall performance of 3 FPS for 2000 particles was presented. These two studies are promising in accuracy, but using the entire needle as the image template and having hyper-parameters necessitates a substantial number of scans; thus, simplifying this process would enhance computational performance.

Neural network applications are also available in the literature as an alternative to classical image processing methods. Faster Region-based Convolutional Neural Network (Faster-RCNN) was applied for the segmentation of the suture needle, and

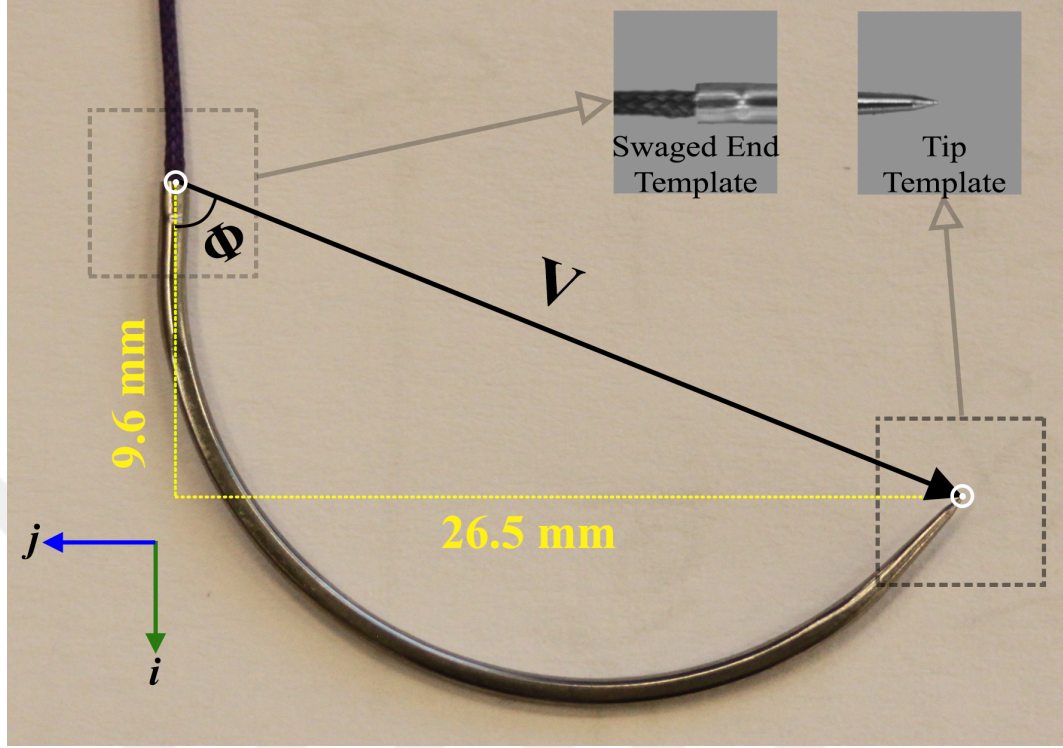


Figure 8: The reference frame of suture needle, swaged and tip end templates.

accuracy rates of % 50-65 [40], %90.39 [41] were obtained with 20 FPS performance. Mask R-CNN [42] achieved a similar accuracy rate with very low FPS. Finally, with YOLOv3 [43], a 90% accuracy rate was achieved with 50 FPS performance. However, artificial neural network applications have three problems that limit their applicability. The first is that experts in the field are needed to label the dataset accurately and precisely. Secondly, labeling processes require labeling as a set of points, which takes a long time. Thirdly, needle feature points or the region of interest, output of the neural network, require an additional method scheme to be reconstructed and detect the terminal points of the needle.

3.3 Methodology

Tracking the suture needle from its distinctive features is an excellent strategy to reduce time complexity. There are two distinctive features of the needle: (i) the swaged end where the needle is connected to the thread, (ii) the tip end (see Fig. 8).

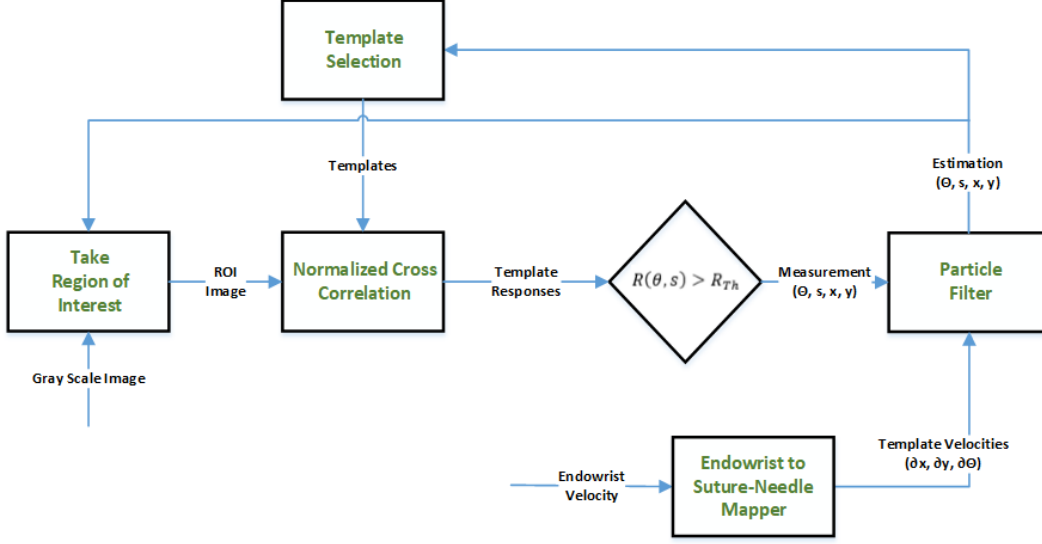


Figure 9: The suture-needle localization pipeline.

Moreover, these features, being reliable indicators for tracking, exhibit similar projections under any 3D rotation of a suture needle when visible. This implies that these features, along with their 3D rotation, can be effectively scanned using templates rotated in 2D space. In this study, fast normalized cross-correlation is used for find the template rotations and their pixel coordinates. This method uses Fourier transform to scan templates. A region of interest (ROI) for each feature is defined to avoid redundancy and possible noise while tracking these patterns.

A template batch T_B has been created to make scanning faster. This template batch contains 360-degree 64x64 rotated templates with 1-degree precision for three scales. Fourier transformations, average values, and standard deviations of the templates in the template batch are pre-processed.

3.3.1 Initialization

Initially, the ROIs of the features are given with user input by marking the pixels in the two camera frame. Since the angle of the templates are unknown, entire image in the ROI is scanned with entire template-batch. The template with achieving maximum score and exceeds the confident threshold is considered as a successful initialization.

Once all the features are initialized, the localization pipe turns into adaptive tracking mode.

3.3.2 Adaptive Tracking

The adaptive scanning method obtains the progression of patterns in sequential frames in a camera image. According to this method, the next templates are found for rotation values between the actual angle of the template $+\gamma_\epsilon$ and $-\gamma_\epsilon$ degrees. The camera image is scanned with the next templates. Among the scanning results, the template with the highest score that exceeds the confidence score is taken as the next template as given

$$(\theta_{best}, \mathcal{J}_{best}) = \operatorname{argmax}(NCC(I(x, y), T(\theta \pm \gamma_\epsilon, \mathcal{J} \pm 1))) \quad (4)$$

where, $I(x, y)$ is the gray-scaled image, and $T(\theta, \mathcal{J})$ is the gray-scaled rotated and scaled template.

3.3.3 Reconstruction

Rotating the suture needle in 3D space, the unit direction vectors of template $\mathbf{i}, \mathbf{j}$ and vector $\vec{v}$ transforms into S_i, S_j , and $\vec{S}_v$, respectively. The direction vector S_i satisfies the following conditions: The angle (ϕ) between the S_i and $\vec{S}_v$, is fixed to 70.2 degrees on the template, this angle does not change due to the rigid body transformations. $\vec{S}_v$ can be computed as $\vec{S}_v = p_{tip} - p_{end}$. The projection of the S_i onto left and right camera planes corresponds to the viewing angles $\theta_{swL}, \theta_{swR}$ of the templates.

The ϕ and the $\vec{S}_v$ are known, then the first constraint can be formed as

$$\vec{S}_i \cdot \vec{S}_v - \cos(\phi) |\vec{S}_i| |\vec{S}_v| = 0 \quad (5)$$

where $\cdot$ denotes the dot product operator. The templates angle are the projection of the $\vec{S}_i$ onto camera plane n_c can be calculated with:

$$proj_{S_i}^c = \vec{S}_i - \vec{n}_c \frac{\vec{n}_c \cdot \vec{S}_i}{\vec{n}_c \cdot \vec{n}_c} \quad (6)$$

where $\vec{proj}_{S_i}^{n_c}$ denotes the projection of vector $\vec{S}_i$ onto camera plane with plane normal n_c .

The scanned template angle θ corresponds to the angle between the projection between the direction vector along the horizontal axis of the camera. This can be formed as:

$$\vec{n}_h \cdot \vec{proj}_{S_i}^C - \cos(\theta)|\vec{n}_h||\vec{proj}_{S_i}^C| = 0 \quad (7)$$

where $\vec{n}_h$ is the direction vector along the horizontal axis of the camera.

$$\vec{n}_h \cdot \vec{proj}_{S_i}^C = \vec{n}_h \cdot \vec{S}_i - \frac{(\vec{n}_h \cdot \vec{n}_c)[\vec{n}_c \cdot \vec{S}_i]}{\vec{n}_c \cdot \vec{n}_c} = \vec{n}_h \cdot \vec{S}_i \quad (8)$$

Combining equations 7 and 8 and normalizing the vector projected on the camera screen $\vec{proj}_{S_i}^C$, the equation becomes:

$$\vec{n}_h \cdot \vec{S}_i - \cos(\theta)|\vec{n}_h| = 0 \quad (9)$$

A coefficient matrix, M , of the vector $\vec{S}_i$ was formed using vector to plane projection formulation .

$$M_{3 \times 4} X_{4 \times 1} = \begin{bmatrix} \vec{S}_v^T & -|\vec{S}_v|\cos(\phi) \\ \vec{n}_{Lh}^T & -|\vec{n}_{Lh}|\cos(\theta_{swL}) \\ \vec{n}_{Rh}^T & -|\vec{n}_{Rh}|\cos(\theta_{swR}) \end{bmatrix} \begin{bmatrix} \vec{S}_i \\ |\vec{S}_v| \end{bmatrix} = 0 \quad (10)$$

where X is a 4×1 vector containing $\vec{v}_x$ and norm of the $\vec{v}_x$. The solution of equation 10 is the smallest eigenvalues of the singular value decomposition (SVD) of matrix M , which is equals to S_i . The cross product of S_i and $\vec{S}_v$ equals the S_k of the suture needle due to orthogonality.

As a result, tracking the swaged end and tip end, the position and orientation of suture needle are localized.

3.4 Grasping Pose Estimation

After the suture needle is picked up with need grasper, jaws are assumed to grasp the suture needle perpendicular at a point $1/3$ – $1/2$ of the needle length away from the swaged end with an ideal grip depth (Fig 1-2) [44], [45]. Yet in many experiments, the suture needle slides while gripping, which results that the relative transformation between them becomes unpredictable. Hence, an estimation of the relative transformation matrix between the end-effector and the suture needle is required.

Assuming the reference frame for the system coincides with the robot base frame, the relative transformation from needle holder to suture-needle, (T_e^{sn}), can be formulated as

$$T_e^{sn} = T_e^R T_R^C T_C^{sn} \quad (11)$$

where, T_R^e , T_R^C , T_C^{sn} denotes the homogeneous transformation matrices from robot base to end-effector, from robot base to camera, and from camera to the suture-needle, respectively. The matrices T_R^e and T_C^{sn} are easy to obtain from the forward kinematics of the robot and visually tracked needle pose in the camera frame. In this study, any error induced by the robot kinematics was disregarded. The transformation matrix from the robot base frame to the camera frame can be computed with hand-eye calibration methods or using an external tracking system [46]. In order to increase the accuracy of the experimental results, an NDI Polaris Vega (Northern Digital Inc., Ontario, Canada) optical tracking system was used for external measurements, whose volumetric RMS positioning error is 0.20 mm [47]. Solving T_e^{sn} directly with a single sample often leads to failure due to possible noise from the visual tracking method. Instead, the end-effector was moved while it was grasping the suture needle firmly and the following procedure was used to find the estimate of the transformation matrix, $\hat{T}_e^{sn}$.

1. Position the grasped suture needle visibly for both cameras.

2. Start data collection with visual and optical tracking systems.
3. Apply small motions to the last three joints of the robot to alter the orientation of the needle.
4. Repeat above steps at least $n=4$ times to get persistently exciting measurements [48].
5. Find the transformation estimate using least squares method.

3.5 Experiments & Results

The purpose of suture needle localization experiments is to evaluate the feasibility of autonomous suture applications and measure the overall localization error. The experimental board was configured to obtain the actual data of the suture needle (Fig. 11). First, two magnets were placed inside the board to fix the needle on the experimental board, and then an optical marking tool was attached to the front of the board. The position and orientation of the needle relative to the optical marking tool were recorded using a caliper. The experiment aimed for the suture needle to be visible as the plate, which was manually moved towards the camera, was rotated and translated. Data and frames of the optical marker and camera were recorded simultaneously. During the experiment, 524 frames were collected, and the needle localization algorithm ran on the GPU, achieving approximately 26 FPS performance. Positional error was 1.37 ± 0.65 mm (Fig. 10-a) while rotational error was 1.18 ± 0.66 degrees (Fig. 10-b) for needle localization.

An evident offset error is observable in the error plots. This offset error is primarily influenced by the initial calibration of the needle location, attributed to measurement errors introduced by caliper measurements and offset errors from optical marker tracking. This error could be mitigated through additional calibration to enhance needle localization.

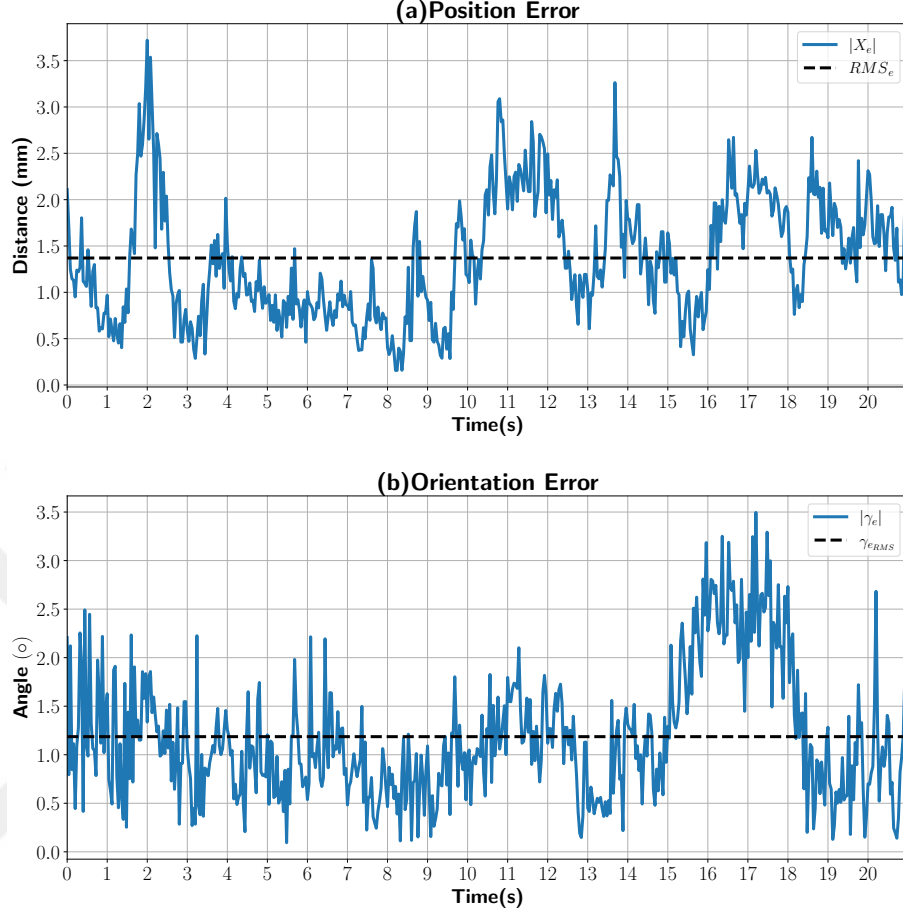


Figure 10: Position and orientation error of suture needle localization experiment.

The precision of the results meets the requirements of suture needle pick-up, insertion, and pull-out tasks. A jaw opening angle of approximately 10 degrees for the needle driver (da Vinci Endowrist Surgical Instrument 420194S) creates a 4.5 mm gap between the jaw tips, sufficient to perform the needle-grasping operation. In addition, the features monitored during the proposed localization method are common features that do not cause differences for all suture needles. Therefore, the proposed method may be used on various suture needle models.

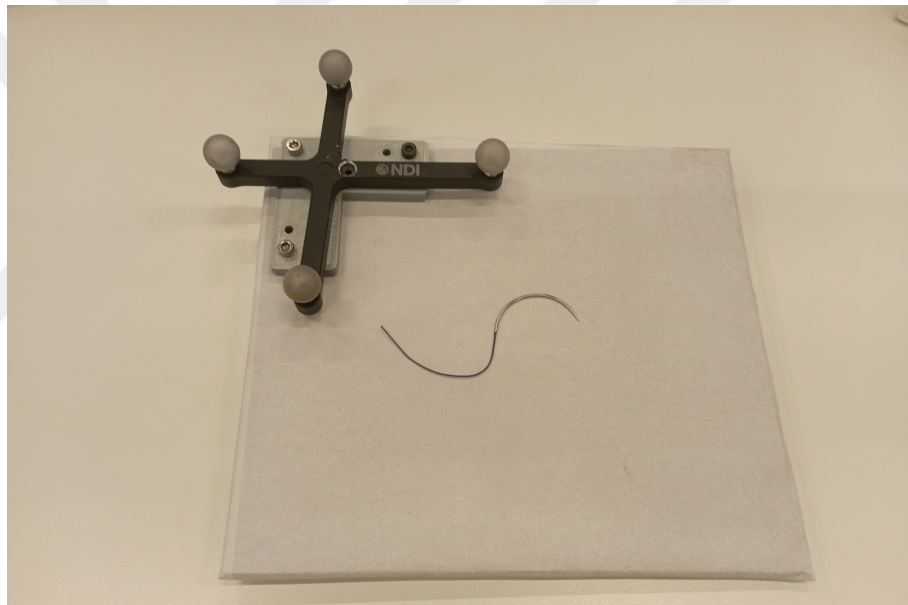


Figure 11: The board used for data acquisition in suture-needle experiments.

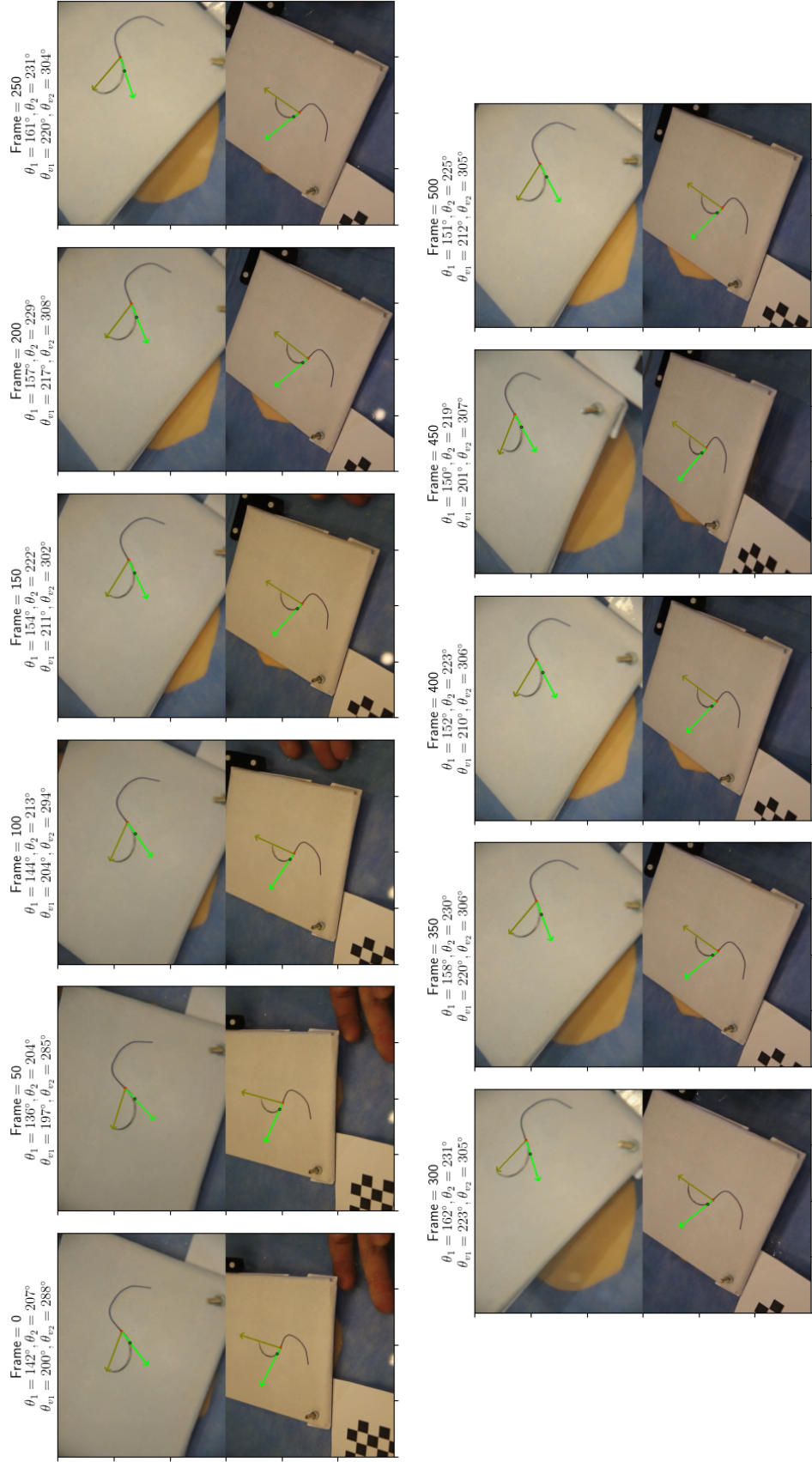


Figure 12: The 2D vectors of the tracking swaged end templates.

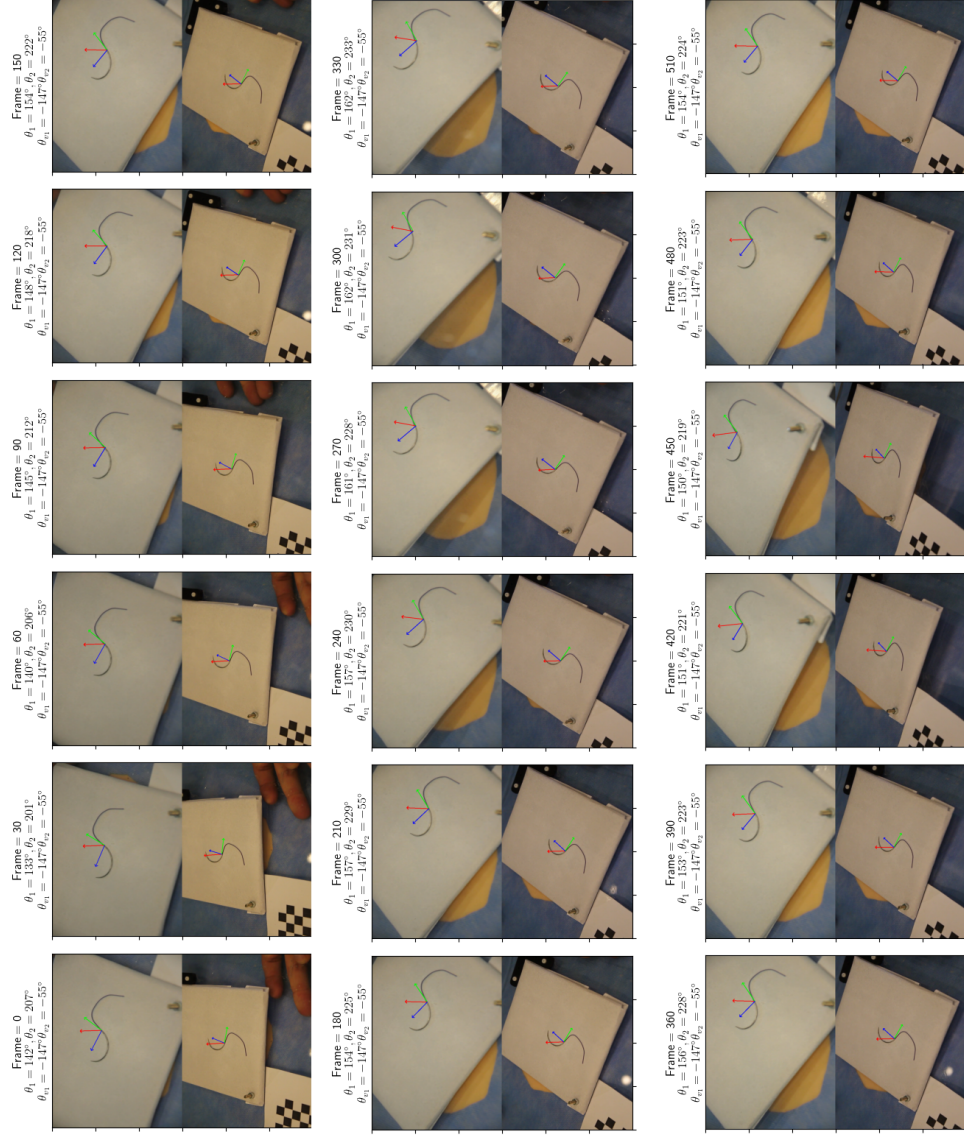


Figure 13: The reconstructed direction vectors of the suture needle.

3.6 Conclusion

The proposed suture needle localization system is novel in that it localizes the suture needle by tracking its subtemplates, which are tip and swaged ends. Exploiting that these ends have similar reflections to the camera frames, these patterns are effectively scanned with 2D rotated templates. The adaptive normalized cross-correlation method is used to measure the matching score. parameters of the multiple-view camera and the geometry of the suture needle are utilized to estimate the pose of the suture needle. The results show that the computation time is significantly reduced while preserving precision; consequently, a GPU implementation of the localization pipeline can process 24 FPS two-camera streams in real-time. Additionally, since the pipeline relies on a swaged end template that includes thread connection, the pipeline is easily applicable in the scenes where the suture needle and thread are together.

CHAPTER IV

SUTURE THREAD LOCALIZATION

In the final steps of the autonomous suturing process, specifically in the knot-tying procedure (Fig 1-g, h, and i), knowledge of the geometry of the suture thread is essential. The thread's appearance frequently changes during the operation due to its deformable and superfine nature. The scenarios pose significant challenges to the visual tracking systems during autonomous suturing, such as self-intersections, partial visibility, occlusion by the surgery tools.

4.1 Literature Review

Jackson et. al performed real-time tracking of suture-thread in stereo-camera frames [49, 50]. The ridge-like features are obtained with the Frangi-Vessellness filter. The noisy features are removed with Gaussian blurring in the orientation domain; then, the blurred points are regressed with Non-uniform rational B-splines (NURBS). The control points of the B-splines are tracked in sequential frames. The RMS error was reported as 1.67 mm. Similarly, Padoy et al utilizes 3D NURBS modelling, Markov Random Field and discrete curve tracking [51] to track suture-thread in camera streams [52]. The average error was reported less than 1 mm in the simple scenarios. The difference between our study and these studies [49, 50, 52] is that the thread is modeled not by its curve but by the discontinuous points detected in the camera image. Hu et. al designed a multi-staged convolutional neural network to extract segmentation, gradient-map, and overlapping map of the suture-thread [53]. The overall precision error reported as 1.09 pixels with color markers and 7.48 pixels without color markers. Lu et. al localized the tip of the suture thread in [54, 55] by employing a design using recurrent neural network (RNN) and long short-term

memory (LSTM). Then; starting from the tip point, the suture-thread is constructed with a fast marching algorithm. The average error was between 0.9 mm and 1.74 mm, depending on the length of the suture-thread. In the subsequent study, Lu et al. report that an architecture with two U-Net architectures in the form of teacher-student requires a small number of labeled data [56]. The main bottleneck of artificial intelligence applications that generate segmentation mask output in this field is the labeling phase of the training data, which requires marking all thread points in the image and is mainly done manually. Differentiating the modeling of the thread can facilitate the automatic segmentation step and opens the possibility of using different AI architectures that make it easier to label the training data.

4.2 Methodology

To segment the suture thread, some assumptions were made regarding the thread's physical properties and the projection of the thread on the camera image. These can be listed as:

1. The thread has a fixed thickness and fixed length.
2. There are at least two distinctive points appearing on each camera view, and they appear in clearly in the camera image. These distinctive points occur because of the projection from $\mathbb{R}^3$ to $\mathbb{R}^2$, and corresponds to intersection, self-intersection or terminal points.
3. The thread has two terminal points in $\mathbb{R}^3$: the first one is attached to the swaged end of the needle, and the second one is the free end.

Appearance of suture thread, existing as a continuous entity in space, transformed into continuous sub-segments in camera frame because of the loss of depth perception. These sub-segments lied between distinctive pixel points which were typically terminal ends or intersection points. Conveniently, the general pattern of the thread in the

camera frame was a series of distinctive points from the swaged end to the free end of the thread, where the distinctive points were connected to each other with one or more curvilinear paths. The model was effectively represented with a directed graph whose edges were the curvilinear paths and whose nodes were distinctive suture-thread points (intersection, self-intersection, and terminal points). This modeled graph would have at least two nodes representing the starting and ending points of the suture thread. The following outlines the localization pipeline for the corresponding suture thread model.

4.2.1 Identification of the distinctive points

In the camera view, the distinctive points on the suture thread breaks the smooth curvilinear edge structure. Thus, the distinctive points were low-confidence keypoints with specific thickness. These points were sufficiently traced with a scoring function, given in 12, similar to the well-known corner response function [57] in literature.

$$R = |\lambda_1 \lambda_2| - k(|\lambda_1| + |\lambda_2|) \quad (12)$$

where λ_1 and λ_2 are the eigenvalues of the Hessian matrix of the image, and k is the confidence parameter that measures the similarity of the point to the corner point.

To guarantee the extraction of all distinctive points, the confidence parameter was set to a small value, $k = 0.005$, and the identification point set had positive response values.

$$\mathcal{N}_I = \{ (x, y) \mid R(x, y) > 0 \ \forall x, y \in R \} \quad (13)$$

The set $\mathcal{N}_I$ contained the distinctive and non-distinctive points which were intermediate points located on the continuous segments. The non-distinctive points were removed during the graph simplification step. Thus, the distinctive points of the thread were identified.

4.2.2 Extracting curvilinear edges and the movement cost map

The continuous curvilinear edges of the suture thread with particular thickness and length were obtained with the well-known HFV filter [58], which amplifies the curvilinear structures in the image frames. Usually, the HFV combines the filter responses for a thickness interval. Applying the HFV filter once was sufficient, under the assumption that the thickness of the suture-thread remains constant in the camera frame. The curvilinear edge vectors were defined with the magnitude of HFV filter response and the direction of the Hessian unit eigenvectors as in (14).

$$V(x, y) = V_o(x, y)\hat{H}(x, y) \quad (14)$$

where $V(x, y)$ is the curvilinear structure vectors, $V_o(x, y)$ is the response magnitude of HFV filter and $\hat{H}(x, y)$ is the unit Hessian eigenvectors. Using the curvilinear structure vectors the movement score map, S_m was acquired through a dot product in (15), yielding a similarity metric between two adjacent curvilinear vectors.

$$S_m(x, y) = \max(V(x, y) \cdot V(x \pm 1, y \pm 1)) \quad (15)$$

Similarly, the movement cost, C_m , and movement vectors, V_m , were computed with (16).

$$C_m(x, y) = e^{-\frac{S_m(x, y)}{\alpha_m}} \quad (16)$$

$$V_m(x, y) = S_m\hat{H}$$

where α_m serves as an adjustable parameter for implementation flexibility which scales the cost value; in the experiments, its value was empirically set to 0.5. The score function amplified the similarity between adjacent vectors when they have similar directions. An example of the outputs of the movement cost function was given in Fig. 14-d. The cost function C_m created a map to calculate and represent the transition and shortest path from one pixel to another.

4.2.3 Computing the shortest curvilinear paths

The simultaneous breadth-first search (BFS) algorithm (given as Algorithm 1) establishes the shortest paths between the nodes. This algorithm has a process queue, a path queue, a visit map, and a best path map. The process queue Q contains triplets of ancestor node, ancestor path, and the pixel coordinate to be explored. The path queue contains the completed paths Q_c ; the visit map keeps the node ID that explored the corresponding pixel coordinate. The best path map contains the paths with minimum movement cost for the corresponding pixel. Initially, the process queue Q is filled with the triplets of input nodes, adjacent pixels of the node, and an empty path object. At each iteration, a triplet of ancestor node, pixel, and path (N, P, T) is dequeued from the process queue; the cost of traveling the pixel P via path T is computed by adding the movement cost of pixel P to the cumulative movement cost of T . A complete path candidate exists if the pixel P is visited by a node different from the ancestor node N . A pair of path T and the element of best path map for the corresponding pixel is queued to the path queue Q_c . If the pixel P is not explored or a better cumulative movement cost is achieved, the new triplets are queued to the process queue. The new triplets are generated with ancestor node N for each adjacent pixel of pixel P and a new path inherited path from T . This iteration continues until the process queue is empty.

The algorithm's inputs are the movement cost map and the pixel coordinates of the nodes. Starting from the input nodes, the algorithm simultaneously explores the paths coming out of the nodes by traversing through all the pixels, and finds the shortest path between the nodes by minimizing the cumulative movement cost.

Consequently, the shortest curvilinear paths among node connections were identified using this algorithm. Example outputs of this step are given in Fig. 14-g.

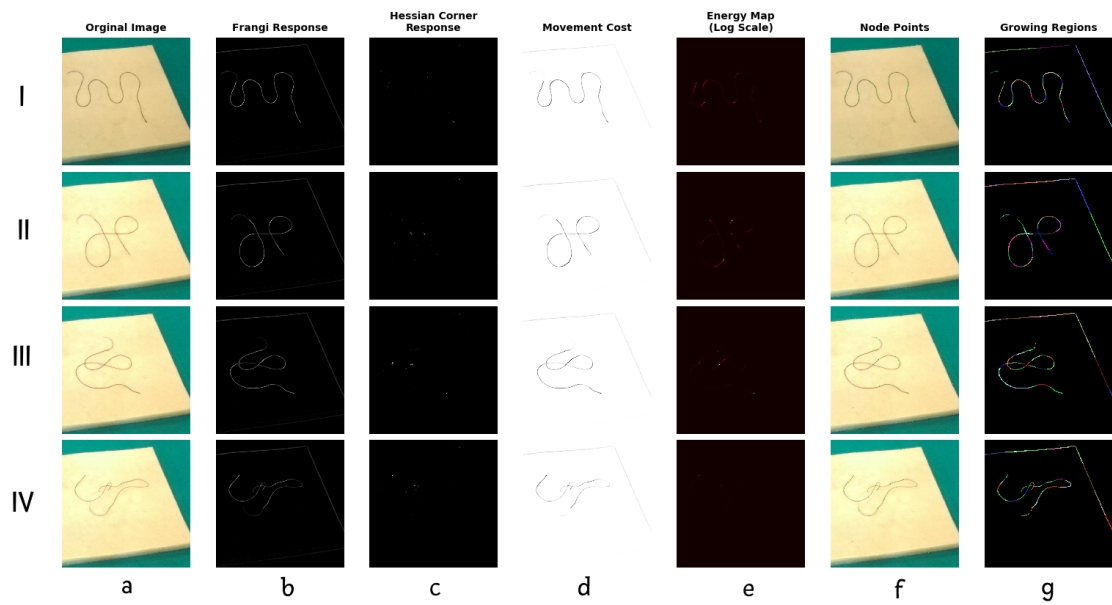


Figure 14: The steps of suture-thread segmentation pipeline.

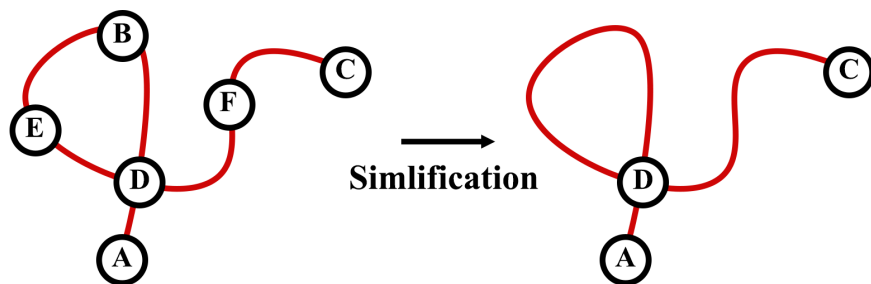


Figure 15: The visualization of graph simplification by removing intermediate nodes.

4.2.4 Simplifying the node-edge graph

The presence of non-distinctive nodes among the input nodes created intermediary nodes, which function as bridge pathways between the distinctive nodes. Non-distinguishing points have only two paths, as they were located in the continuous segment of the thread. The node-edge graph was simplified by removing the intermediary nodes, and the two paths of the removed node were connected together. The simplified node-edge graph included only distinctive nodes and their connections. The example simplification is illustrated at Fig. 15 by removing the intermediate nodes B-E & F.

4.2.5 Discriminating the suture thread

This simplified node-edge graph included graphical representations of curvilinear objects formed as chains of connected nodes. The chain belonging to the suture-thread must be discriminated to localize it correctly. The suture-thread tended to bend during suturing due to its pliability. The directions of the consecutive vector on the suture thread segment changed along the length and is measured by the cross product (17). This direction change is an additional characteristic of the thread segments that differ from the other curvilinear segments.

$$S_e(x, y) = \min(V_m(x, y) \times V_m(x \pm 1, y \pm 1)) \quad (17)$$

where the $V_m(x, y)$ is movement vectors, $S_e(x, y)$ is the score and $\times$ sign denotes cross-product operator. An example output of the direction displacement function is shown in Fig. 14-e.

The directional energy of an edge was determined by calculating the mean of the directional energies of all pixels along that edge. Nodes with highly energized edges were identified as suture-thread nodes. Starting from the first node, which belongs to the swaged end N_0 of the suturing needle, the sequence of connection of the path was travelled by passing through all high-energy nodes and the paths were connected to

distinctive nodes. In scenarios where multiple path option exist during traversal, the path with the minimum direction difference was selected. Thus, the node-edge chain representing the suture thread from its start to end was formed.

4.2.6 Reconstructing the Suture-thread

The node-edge chain of the left camera frame $\mathcal{C}_L$ and the node edge chain of the right camera frame $\mathcal{C}_R$ were matched by their node order in their chain.

$$\begin{aligned}\mathcal{C}_L &= [N_{L_0} \ T_{L_0} \ N_{L_1} \ T_{L_1} \ \dots \ T_{L_m} \ N_{L_m}] \\ \mathcal{C}_R &= [N_{R_0} \ T_{R_0} \ N_{R_1} \ T_{R_1} \ \dots \ T_{R_n} \ N_{R_n}]\end{aligned}\tag{18}$$

The partial or full reconstruction of the suture thread is based on the matching the nodes by their structural similarity, which is their edge count and edge type (self-loops or regular). Starting from the first nodes of the two view N_{L_0}, N_{R_0} , the nodes matches in the chain are paired until first pair of unmatched node discovered or the chain is finished. If a unmatched node pair is discovered, the matching procedure is ended.

$$\mathcal{P} = \begin{bmatrix} N_{L_0} \leftrightarrow N_{R_0} \\ T_{L_0} \leftrightarrow T_{R_0} \\ \vdots \\ N_{L_k} \leftrightarrow N_{R_k} \\ T_{L_k} \leftrightarrow T_{R_k} \end{bmatrix}\tag{19}$$

The terminal point of matched edges are interpolated to align their terminal points and reconstructed with triangulation method. Example illustrations of the reconstruction are shown in Figs. 18 & 16.

4.2.7 Interpreting the graph

In this representation, it is possible to extract structural node attributes by their edge counts. For example, the terminal nodes of the suture thread have 1 edge because there is only one moving direction is available. On the nodes located on

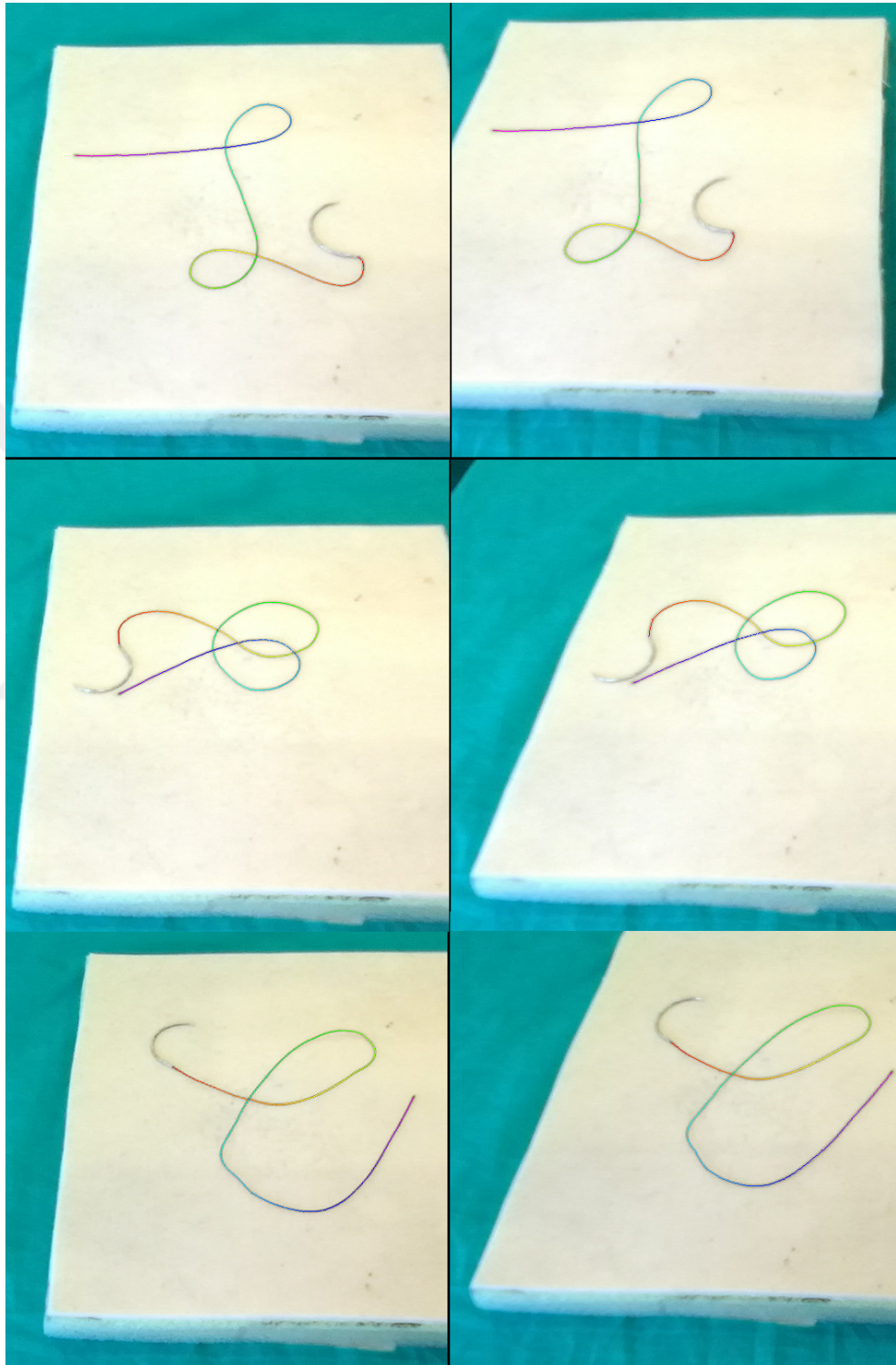


Figure 16: Illustration of matches of suture thread points in stereo-view.

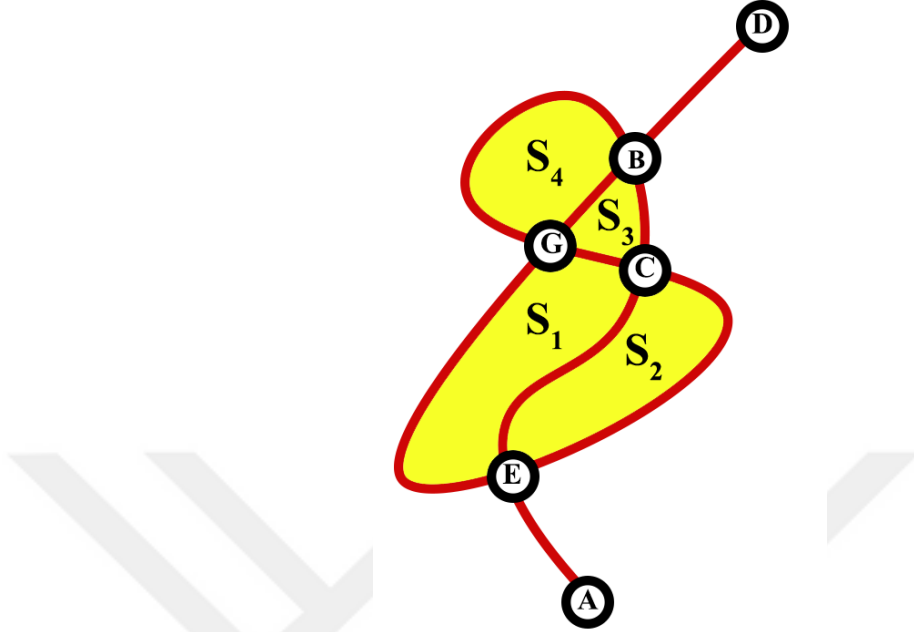


Figure 17: The figure illustrates the contours which surrounded by nodes of the suture thread.

self-intersection of suture thread, there are even numbers of edges (See Figs. 17, 15, 18).

The contour between knots and connection edges facilitates checking whether a suture thread forms a knot. Knots are likely to form when the suture thread passes through a contour in the chart. Examining the 3D plane of these contours makes it easier to check whether an edge passes through a gap, which allows us to interpret the pattern of the suture knot effectively.

An example illustrated in the 17. In the figure, the contours are shown with yellow color with names S_1, S_2, S_3, S_4 . The 3D plane of these contours can be easily computed with linear regression to points of nodes and the edges which creates the contour. The edges that pass through a contour can find by checking the adjacent edges of the nodes covers the contour. For example, the edges between G-B, G-C & C-E are candidate edges passing through the surfaces $S_4 \cup S_3$, $S_3 \cup S_1$ and $S_1 \cup S_2$.

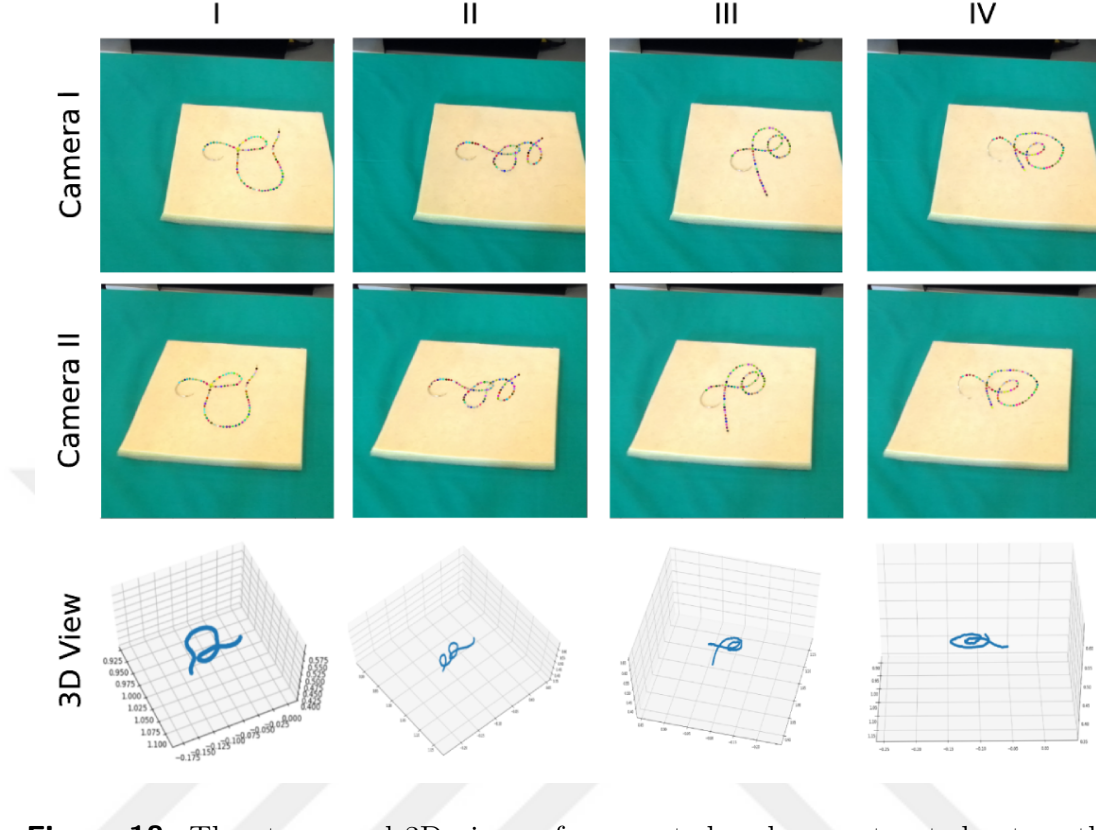


Figure 18: The stereo and 3D views of segmented and reconstructed suture-thread.

4.3 Experiments & Results

In the suture-thread detection experiments, three suture threads with known length is put in various shapes where experiments gradually increase their occlusion counts. The purposes are comparing the reconstruction length error and interpreting the algorithm's performance over the occlusion count. The estimated suture-thread length is taken as

$$L = \int_{t_a}^{t_b} \sqrt{\left(\frac{dx}{dt}\right)^2 + \left(\frac{dy}{dt}\right)^2 + \left(\frac{dz}{dt}\right)^2} dt \quad (20)$$

where t_a and t_b denotes the terminal suture-thread points. The sample views are illustrated in 18. Numerically, the average of estimations is given in the 2. In the table, the number of distinctive points includes the two terminal points of the suture thread, which means there is no occlusion or self-intersections if the distinctive points is equals to 2.

Table 2: The estimated suture-thread lengths over number of distinctive points.

	Number of distinctive points		
	2	3	4
Actual Length (mm)	Estimated Length (mm)		
75	73.8 ± 4.5	77.2 ± 2.1	-
100	104.5 ± 7.3	95.7 ± 3.8	98.8 ± 1.4
150	157.3 ± 18.1	154.6 ± 13.7	149.1 ± 3.9
Mean Error (mm)	3.8	≈ 1	≈ 1
Error percentage(%)	4.11 ± 10.7	$\approx 1.1 \pm 7.04$	$\approx 1.1 \pm 2.8$

The results show that the proposed pipeline is promising over occlusion count. The underlying reason is that the reconstruction method of thread segments is based on the interpolation between matched nodes. The number of occlusion counts decreases each sub-thread segment’s length, resulting in an interpolation error.

4.4 Conclusion

The solution developed for the second problem addressed, namely the visual localization problem of the suture thread, encompasses a novel pipeline based on setting up an association between the node-edge graph and the suture thread’s camera view. This association converts the distinctive points of the suture thread where the continuous edge structure is broken to the nodes and curvilinear continuous thread segments to the edges of the graph. These distinctive points are detected by obtaining the low-confident corner points using a corner response function. The curvilinear and continuous thread segments are extracted as the shortest paths of a movement map utilizing the HFV filter. The similarity of segments to the thread is scored with a novel function based on the direction change on the thread. The suture-thread is reconstructed by matching the node-edge chain in the two graphs created for two camera images. The results show that the proposed pipeline is a powerful alternative that can reconstruct the suture thread precisely in complex views. Moreover, since

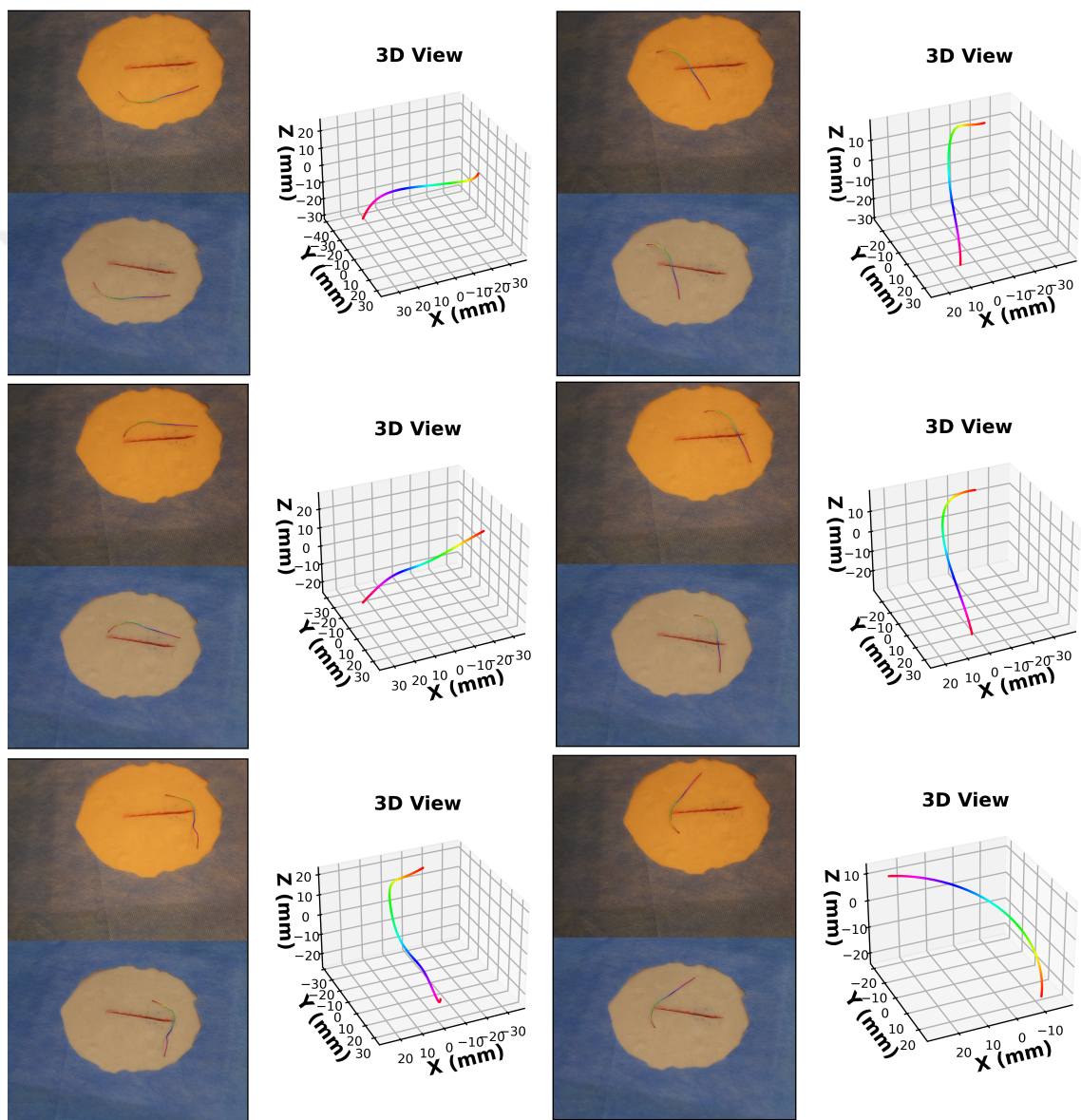


Figure 19: The segmentation and reconstruction examples of 75 mm suture thread.

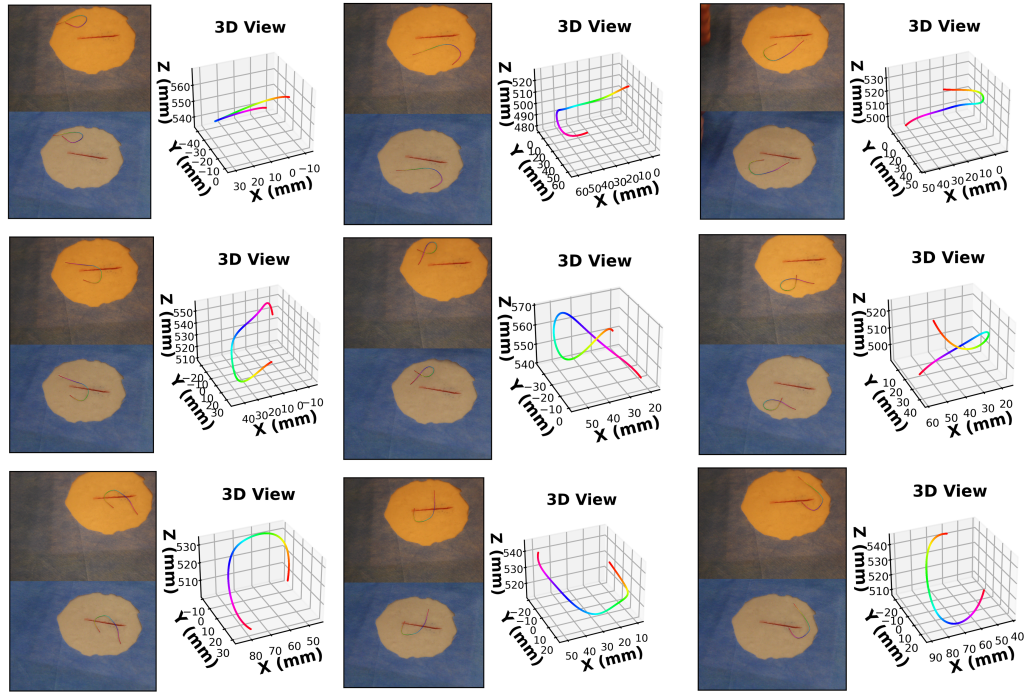


Figure 20: The segmentation and reconstruction examples of 100 mm suture thread.

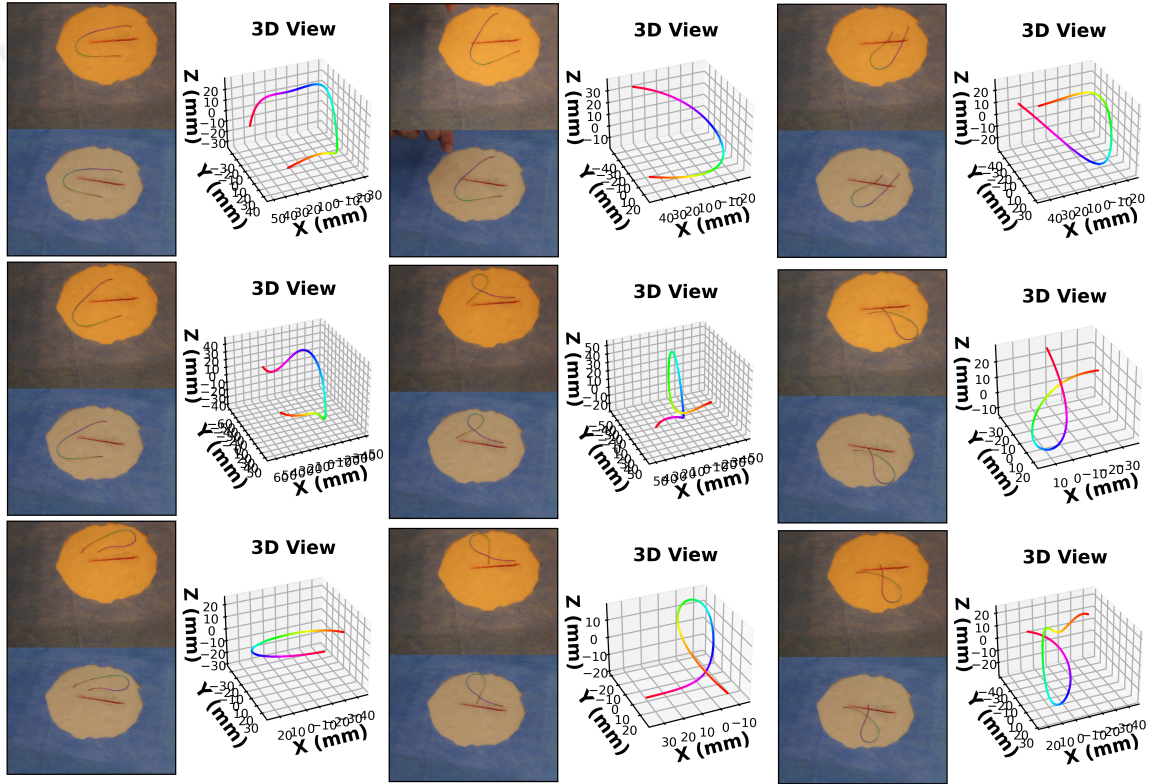


Figure 21: The segmentation and reconstruction examples of 150 mm suture thread.

the pipeline does not include thresholding, it eliminates problems such as pixel disappearance and breaking. Finally, representing the suture-thread view in a node-edge graph enables high-level interpretation.



CHAPTER V

SYSTEM CALIBRATION AND PERFORMANCE OPTIMIZATION

5.1 Robot Joint Offsets Optimization

Surgical procedures often require millimetric precision. This level of accuracy is of utmost importance because even minor deviations can result in patient complications, tissue tears, or operation failure. Therefore, the autonomous suturing robotic system must operate with optimized precision. This optimization process is not only a technical necessity but also a basic necessity for protecting patient health and ensuring the success of the surgical procedure. In serially connected robotic systems, the most severe of these errors are caused by joint offset shifts. These minor errors in joint offsets have a magnified effect on the end controller when used in the kinematic equations of the robot. That is, small link offsets can be disproportionately large in the Cartesian position of the end controller. This can mean the difference between a successful procedure and an unfavorable outcome in a surgical context.

In this context, this section describes the optimization to minimize the Cartesian error caused by connection offsets in the robot end controller. The approach is to measure the Cartesian position at the end of the robot with a high-precision device, and the kinematic configuration corresponding to this Cartesian position is calculated. The high-precise data is collected with the optical tracker with two optical markers M_5 & M_1 was placed on the end of endowrist, and the robot reference frame. The robot joint angles were moved slowly, only one at a time, and marker data and joint angles were recorded. Then, using the equation 23 the T_{Op}^{Rb} is computed. The data of marker M_5 is converted to transformation matrix $\mathcal{T}_{Rb}^{Ee}$ from robot base to end effector



Figure 22: The optical marker(M_5) tool attached to acquire cartesian position of Endowrist.

by excluding the marker tool offset.

$$\mathcal{T}_{Rb}^{Ee} = (T_{Op}^{M_1} T_{M_1}^{Rb})^{-1} T_{Op}^{M_5} T_{M_5}^{Ee} \quad (21)$$

There are multiple kinematics configuration that describes the $\mathcal{T}_{Rb}^{Ee}$. In order to find the valid one among these configurations, we focused on the joints where offsets are least reliable. In our configuration, these least reliable joints picked as four, five six and seven starting from the robot base. The lengths of these joints were written as a symbolic variable, and the cartesian coordinate of the end-effector was derived with forward kinematics equations. Cartesian error is the difference between the symbolic equation and numeric data.

$$P_e = \sum^{Vi} (X_e^2 + Y_e^2 + Z_e^2) \quad (22)$$

The objective is estimating the joint offsets that minimize the error P_e . There are

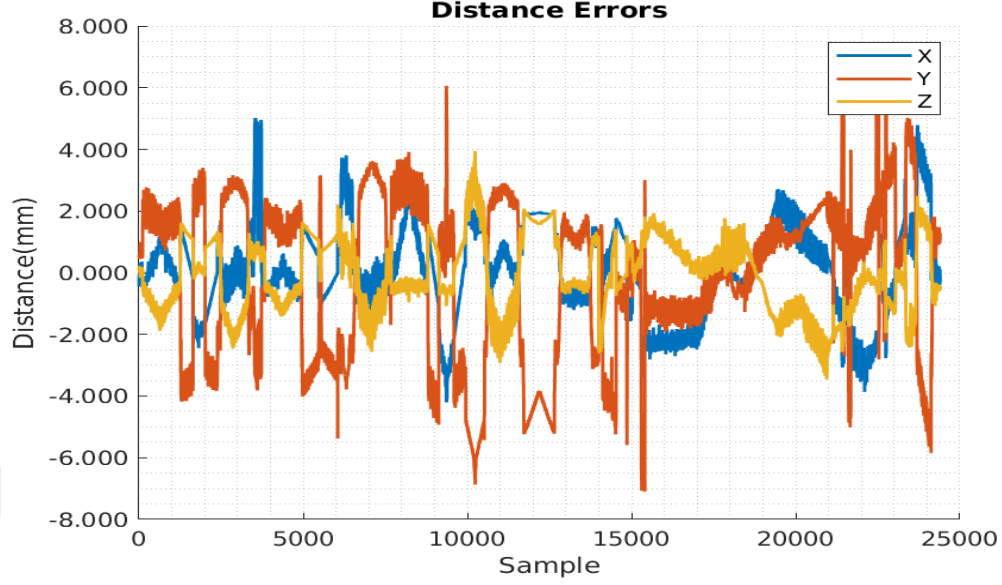


Figure 23: The Cartesian error of optimized forward kinematics.

several optimization methods to minimize the error. The constrained nonlinear optimization in the Optimization Toolbox of MATLAB was used. The minimum loss value was 12.64 mm^2 for approximately 25000 data samples. The mean of the errors was $1 \pm 1.2 \text{ mm}$, $2.2 \pm 2.6 \text{ mm}$, $1.1 \pm 1.5 \text{ mm}$ on axes x, y & z, respectively. The mean of total error was $2.66 \pm 3.3 \text{ mm}$. The x,y, and z errors and the total error are shown in Figs. 23 & 24, respectively. The optimized joint offsets are in the 3.

Table 3: The optimized joint offsets

Joints	Optimized Offsets (m)		
	X	Y	Z
1	0	0	0.1409
2	0	0	0.194
3	0	0	0.1924
4	0.0771	0	0.1221
5	-0.0863	0	0.3893
6	0	0	0
7	0.0863	0.0188	-0.6603
8	0.0479	0.0025	0

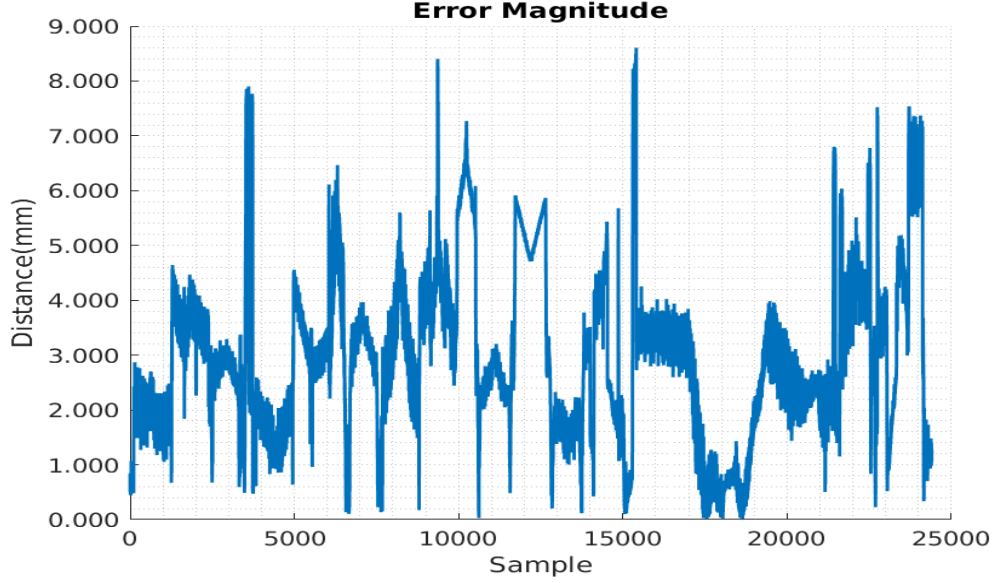


Figure 24: The magnitude of cartesian error after kinematic offset optimization.

5.2 *Multi-view Camera Calibration*

Camera calibration is critical in multiple camera systems to reconstruct 3D objects precisely. The working principle of reconstruction ensures that the pixel coordinates captured on the camera's sensors are converted into three-dimensional points. The reconstruction accuracy depends on the internal camera parameters, which are lens distortion coefficients, focal length, sensor dimensions, sensor count, and external camera parameters, which are rotation and translation of the cameras. Calculating these variables with high precision is very important because it affects the reconstruction accuracy of the object localized in the autonomous suture system. If the calibration is incorrectly done, inconsistencies occur around the movement. For robotic operations where high precision is mandatory, such as automatic sutures, a small error can cause the operation to fail. This calibration process is necessary to ensure the instructions work perfectly with the robot. If this calibration is not done correctly, inconsistencies occur around the movement. For robotic operations where high precision is mandatory, such as automatic sutures, a small error can cause the application



Figure 25: The optical marker(M_2) attached to the head of camera.

to be incorrect. This calibration process is necessary to ensure the instructions work perfectly with the robot.

In our setup, the transformation between the robot and the camera is based on the measurements of optical markers, and a camera calibration process uses a checkerboard pattern. An optical marker is attached to the metal plane that the first robot is placed on (See Fig.2). The transformation between this marker and the robot base T_{M1}^{Rb} is measured from the 3D Cad Models of the metal plate and the robot. The transformation matrix from the NDI device to the first robot frame is equal to:

$$T_{Op}^{Rb} = T_{Op}^{M1} T_{M1}^{Rb} \quad (23)$$

Two markers (M_2 , M_3) are attached to the camera to the head of the cameras with a 3D printed tool as given in Fig. 25. A calibration board is constructed with an optical marker (M_4), and a checkerboard pattern is placed on a plexiglass board

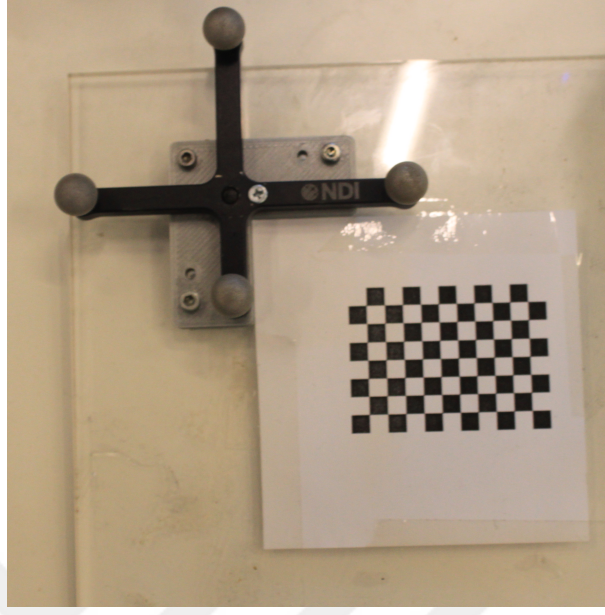


Figure 26: Calibration board with optical marker M_4 and 5 mm checkerboard squares on a plexiboard

(26). The transformation matrix from the optical marker $T_{M_4}^{CB}$ to the start point of the checkerboard is measured using the 3D CAD models of them. The objective of camera calibration is estimating the transformation matrices from the markers M_2 and M_3 to the camera coordinate system. In the camera calibration, the cameras and the checkerboard are put into a visible configuration for the optical tracking device. While the calibration board was moving, the marker data and the pixel coordinates of checkerboard were recorded.

$$T_{M_2}^{C_1} = T_{M_2}^{Op} T_{Op}^{M_4} T_{M_4}^{CB} \mathcal{T}_{CB}^{C_1} \quad (24)$$

Here, $\mathcal{T}_{CB}^{C_1}$ is the transformation matrix from the checkerboard to the camera center, and it corresponds to the checkerboard pose detected in the camera frame. The pose detection is obtained with Open-CV library functions. The mean of the $T_{M_2}^{C_1}$ gives the estimation result. These steps are repeated for the second camera with M_3 marker, and then both transformation matrices are estimated. Finally, the object Q detected

in the camera system can be described in the robot system as :

$$T_{Rb}^Q = T_{Rb}^{Op} T_{Op}^{M_2} T_{M_2}^{C_1} T_{C_1}^Q \quad (25)$$

where $T_{C_1}^Q$ is the transformation matrix composed with detection results.



CHAPTER VI

CONCLUSION AND FUTURE WORK

6.1 Conclusion

This thesis addresses visual localization problems of an automated suturing system with a holistic design consisting of detection and tracking systems for the tissue cut, suture needle, and suture thread. The role of these surgical equipments in autonomous suturing, challenges, and the requirements of the visual tracking are discussed in detail. The localization designs are detailed, address the requirements, and are robust against the challenges.

The tissue cut localization pipeline combines a line detector and a U-Net-based neural network for segmentation, a novel implementation for tissue cut localization. The tissue cut's ray is reconstructed, and its length and the terminal points are estimated. The operation plan for given surgical parameters is automatically constructed to fulfill the first step of autonomous suturing. The experimental results show that the given pipeline is applicable when the tissue is fixed. This pipeline is the basis for automatic suture planning, which can be improved.

The proposed suture needle detection and tracking pipeline is based on a strategy that tracks the sub-templates of the suture needle, which are swaged and tip ends. A feature of these sub-templates is introduced and exploited to perform tracking with fewer parameters with the adaptive normalized-cross-correlation method. This strategy is a flexible design for different types of suture needle models since those sub-templates are standard parts. The pipeline is tested with the optical marker data collected with an experiment board. Compared to the state-of-the-art pipelines, the proposed pipeline has achieved higher FPS performance than literature studies

with millimetric precision and keeping the flexibility of the design. The numerical data shows that the average error is less than 1.5mm, which is suitable for surgery applications. The detection and tracking system can track the suture needle in real-time with two cameras with 24 FPS streaming capacity.

The presented suture thread detection mechanism detects the suture thread image on the camera using a node-edge graph, where the nodes are depicted as distinctive points and the edges as curvilinear paths. Nodes in the node-edge graph are defined as places where the tube structure in the camera image is distorted and detected with the corner finding function. The edges in the graph is taken as Curvilinear paths extracted using the Frangi Vessellness filter. The shortest connections of nodes are found using the movement map. A novel similarity score determined the similarity between the edges and the suture thread. Node-edge graphics in different camera images are extracted separately and matched by looking at the node structure, and reconstruction is provided. The findings obtained from the experiments confirm that this localization pipeline works robustly and sensitively against frequently occurring patterns (thread knots and self-intersections) during autonomous suturing. The created node-edge graphs provide a basis from which the nodes and thread direction can be easily determined. Finally, concepts such as camera calibration, analysis of the relative coordinate system, minimization of errors due to kinematic configuration, and other issues of autonomous suturing systems consisting of dual robotic arms are addressed.

6.2 *Future work*

The tissue cut localization pipeline has been implemented to work with realistic silicone tissues as much as possible. These tissues have a high resemblance to real tissue, so it is envisaged that the system can be used in surgical operations. In future work, the neural network can be trained with real tissue cut images, and its scope of

application can be extended to surgical procedures.

The suture-needle localization pipeline could be integrated with optical flow or improved a faster template updating strategy [59]. This would ease the burden of the scanning for next templates (see (4) in the frames which is the most time consuming computation for this system. Also, applying parallel computation or embedded systems to the localization pipelines can improve the performance of the complete design.

In the current system, camera calibration takes a long time and is valid for static positions. To speed up this process, auto-calibration methods or adaptive calibration methods can be developed, thus facilitating the experimentation process and improving the robustness against possible camera movements.

Additionally, a detection mechanism can be developed to verify that the grasping status of the suture needle. The status of grasping would be a useful data to verify the success/failure of the steps of the autonomous suture especially in pick-up. In this way, these steps could be persistently repeated for success. Finally, exercising control over camera focus, employing endoscopy cameras or surgical camera lenses, can minimize the error margin of the entire system.

CHAPTER VII

APPENDIX

Algorithm 1: Multiple source node breadth first search algorithm (MSBFS).

```
1 Function MultiSourceBranchFirstSearch(Graph  $G$ , Node[]  $N_s$ ):
2    $Q, Q_C$  are empty queues
3    $V_s, V$  are empty matrices
4   for each node  $N$  in  $N_s$  do
5     for each neighbour pixel  $(y, x)$  of  $N$  do
6       if  $G[y][x] \neq \infty$  &  $V[y][x] = -1$  then
7          $T \leftarrow \text{Edge}(y, x, G[y][x], \text{source} = N)$ ;
8          $Q.\text{insert}(T)$ ;
9          $V[y][x] \leftarrow N.\text{id}$ ;
10         $V_s[y][x] \leftarrow T$ 
11  while  $!Q.\text{empty}()$  do
12     $P \leftarrow Q.\text{get}()$  ;
13     $\text{id} \leftarrow P.\text{id}$ ;
14    for each neighbour pixel  $(j, i)$  of  $P$  do
15      if  $V[j][i] = -1$  then
16        if  $G[j][i] \neq \infty$  then
17           $\text{cost} \leftarrow G[j][i] + P.\text{cost}$  ;
18           $T \leftarrow \text{Edge}(j, i, \text{cost}, \text{parent} = P)$ ;
19           $Q.\text{insert}(T)$ ;
20           $V[j][i] \leftarrow \text{id}$ ;
21           $V_s[j][i] \leftarrow T$ ;
22      else if  $V[j][i] = \text{id}$  &  $P.\text{cost} + G[j][i] < V_s[j][i]$  then
23         $V_s[j][i].\text{parent} = P$ ;
24         $V_s[j][i].\text{cost} = P.\text{cost} + G[j][i]$ ;
25      else
26         $R = V_s[j][i]$ ;
27         $Q_C.\text{insert}([P, R, P.\text{cost} + R.\text{cost}]);$ 
```

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