Christian Kunz*, Maria Kraus, Rayan Younis, Martin Wagner, and Franziska Mathis-Ullrich

Statistical Shape Models for Grasp Point Determination in Laparoscopic Surgeries

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Abstract: Robotic assistance systems are being used more and more frequently in the operating room, with the goal to support surgeons and to automate parts of a procedure. The laparoscopic cholecystectomy is one of the most common procedures in Germany. We aim to automate the assistant grasp task in this procedure. To achieve this goal, first the grasp points on the gallbladder need to be determined. In this work, we therefore present a statistical shape model fitting to the gallbladder for grasp point determination. Gallbladder and liver point clouds are utilized as inputs. A registration algorithm is used to fit the shape model to the gallbladder mesh. The process is evaluated on three different datasets achieving a successful grasping point identification of 90% for artificially created gallbladders, 100% for our silicon phantom model, and 90% for ex-vivo organs.

Keywords: Grasp Point Determination, Statistical Shape Models, Cholecystectomy, Robot-assisted Surgery

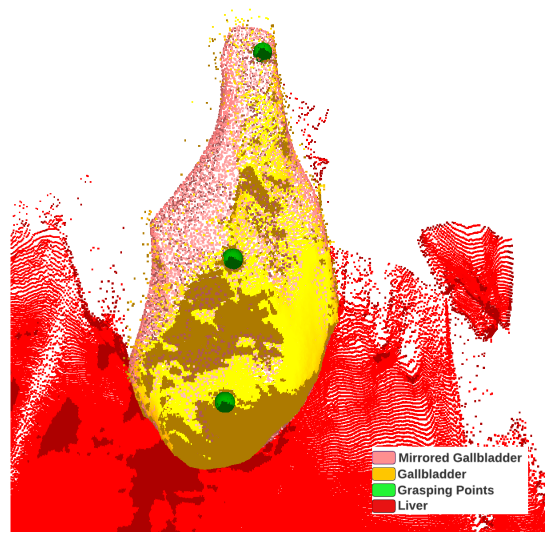

Fig. 1: Results of grasp point determination on a surgical phantom.

1 Introduction

Robotic systems are increasingly becoming an important part of modern surgical procedures, as they offer greater precision and stability. One of the critical challenges in cholecystectomy is the accurate identification of grasp points on the soft tissue, which is essential for successful surgical manipulation. This paper explores the application of statistical shape models (SSM) to address this challenge. SSMs, which have been extensively used in various medical imaging and analysis tasks [1], offer a robust framework for understanding and predicting anatomical structures from complex datasets.

Sarkalkan et al. [2] investigated how statistical shape models can be applied to bones for the study of osteoarthritis development, accuracy improvement for the prediction of bone fractures, the design of orthopedic implants, and surgical planning. Lüthi [3] investigates the creation and usage of statistical shape models from a machine learning perspective, as well as their application in the planning of cranio-facial surgeries. Han et al. [4] utilized preoperative CT scans and Active Shape Models to perform an automated trajectory planning for pelvic trauma surgery. Kunz et al. [5] introduced an approach were two SSMs were used for autonomous planning of catheter placements in neurosurgical interventions, like the ventricular puncture. The shape models were utilized to determine the entry points on the skull and target points inside the ventricular system. The puncture trajectory was visualized with an augmented reality headset. Frangi et al. [6] developed a statistical shape model (SSM) of the left and right ventricles of the heart using MRI data. They began by constructing an atlas of the ventricles, then automatically extracting landmarks from it. Finally, a volumetric nonrigid registration technique was used for the model fitting.

In this work we present an approach to create a statistical shape model from data and fit it to the gallbladder for the determination of grasp points. We reach high accuracy values and find a valid grasp point in at least 90% of cases.

***Corresponding author: Christian Kunz, Franziska Mathis-Ullrich,** Friedrich-Alexander-Universität Erlangen-Nürnberg, Department of Artificial Intelligence in Biomedical Engineering (AIBE), 91052 Erlangen, Germany, E-Mail: franziska.mathis-ullrich@fau.de, christian.kunz@fau.de
Maria Kraus, Intelligente Prozessautomation und Robotik (IPR), Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany
Rayan Younis, Martin Wagner, Department of Visceral-, Thoracic and Vascular Surgery, Faculty of Medicine, University Hospital Carl Gustav Carus & Center for the Tactile Internet with Human in the Loop (CeTI), Technische Universität Dresden, 01307 Dresden, Germany, E-Mail: martin.wagner@ukdd.de

2 Materials & Methods

In this chapter we provide an overview of the methods for grasp point determination on a gallbladder. Our method uses point clouds as input from three different scenarios: virtual models, a phantom, and ex-vivo porcine livers.

2.1 Statistical Shape Model Creation

First, we created gallbladder and liver models based on recorded point clouds from ex-vivo experiments. The phantom that was used in this work was presented by us in [7]. It is based on the same virtual gallbladder models that were artificially created. We randomly deformed the gallbladder model with Open3D [8] to create 30 realistic pig gallbladders, to reflect shape variations that can be found in reality. The framework Scalismo is used in this work to create and fit the statistical shape model. The SSM of the gallbladder was generated from the created dataset. To create the SSM, a Point Distribution Model was chosen, where all parameters are automatically derived from the dataset:

$$x = \bar{x} + Pb \quad (1)$$

where x is the vector of landmark positions that represent the shape of an object, $\bar{x}$ represents the mean shape, P is a matrix of eigenvectors obtained from the principal component analysis and b is a vector of shape parameters that weigh the contributions of each principal mode of variation to the specific instance of the shape. The grasp points are defined manually on the shape model. We define three grasp points as an example to represent different grasp positions for different stages of the gallbladder removal. They are defined on a vertex point of the mesh. Additionally we define 18 landmarks on the surface of the gallbladder as depicted in Figure 2 d). The landmarks are used as anchor points and we want to register them to the corresponding points on the target mesh. These are additional points to reach correspondence. This is especially useful for organs with few points of interest or features.

2.2 Shape Model Fitting

In a first process step, a semantic segmentation is carried out to semantically segment the recorded point clouds. We have presented an approach in [9]. Each point in the point cloud is classified as gallbladder, liver, or background. The method presented in this paper only takes the points of the gallbladder into account.

In this work, we investigate fitting a SSM to a target mesh. Statistical shape models are represented as surface meshes. Several preprocessing steps need to be carried out to prepare our input point clouds for the fitting procedure. This involves the correction of the orientation and completion of the gallbladder. Further, a mesh is generated from the given points and a landmark determination is carried out. The whole preprocessing workflow is depicted in Figure 2.

2.2.1 Preprocessing

First the gallbladder is oriented with Open3D on the x,y plane and in positive z-space as depicted in Figure 2 a). We assume that the camera captures the gallbladder from above, so that the liver and the gallbladder are visible.

First, a bounding box is created based on the given point cloud of the gallbladder. To ensure that the gallbladder is oriented upwards, a line is calculated that starts in the center of the point cloud and points in positive z-direction. If the line intersects with the points, the point cloud is rotated by 180°. To orient the gallbladder correctly on the x,y plane in positive x-direction, two helping planes are constructed to measure the thickness of the point cloud at 25% and 75%. Through surgical knowledge we know that the fundus of the gallbladder is larger than its neck. The gallbladder is then rotated so that the neck points to the right (positive x direction).

As the point cloud is only visible from one side, we thus need to reconstruct the whole body of the gallbladder. In the next steps we reconstruct the oriented point cloud to its estimated full shape. We take surgical knowledge about the volumetric shape of the gallbladder into account. First, a help plane is created that is parallel to the x,y plane. We assume that approximately half of the gallbladder of one side is visible. We calculate the center of the recorded point cloud and translate the help plane to this position. We then mirror the points to get a partial full shape of the gallbladder by computing the distance of every point to the mirror plane and creating a mirrored point on the other side of the plane. In a consecutive stage, we need to fill all shape holes and construct a surface mesh. We do so by using the Open3D alpha shape algorithm implementation [10]. To obtain better fitting results, landmarks are determined on the target mesh. These points are used as anchor points, where corresponding points on the SSM and on the target mesh are aligned as closely as possible. To do so, we construct two help planes parallel to the x,y and x,z planes, respectively, orthogonal to each other. We then move a third orthogonal z,y plane over the gallbladder from the neck to the fundus and create on six positions landmarks: One point at the fundus and the neck, and four points at 20%, 40%, 60%, and 80% respectively. We create a point at each side of the gallbladder (+z,-z,+y,-y) where the distance to the center point of the z,y plane is maximized. This is visualized in figure 2 d).

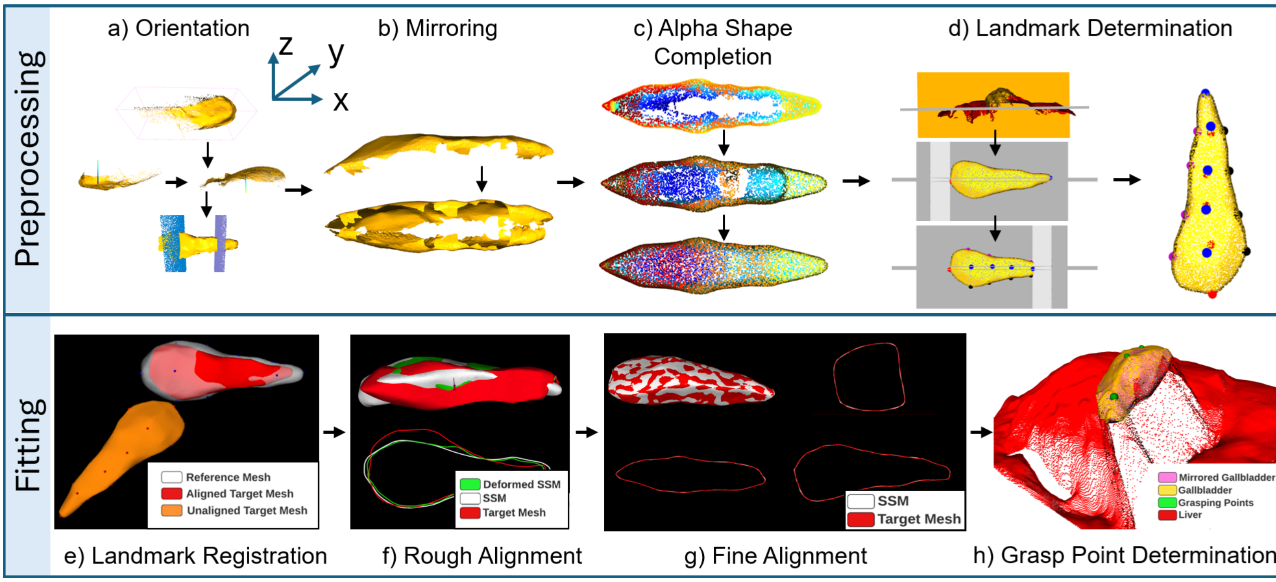

Fig. 2: Process of the shape model fitting.

2.2.2 Shape Model Fitting

After preprocessing, the fitting process is carried out. The shape model fitting consists of several consecutive stages. First, a rough alignment is performed to provide a suitable initial fitting. Next the fine alignment is done to match the shape model as closely as possible with the target mesh. In the last step, the grasp points are determined.

The initial rough alignment consists of two stages. First, the landmarks of the shape model mesh and the target mesh are rigidly registered to each other without deforming the shapes using Open3D. In the second stage a gaussian process regression (GPR) is performed. GPR is a flexible non-parametric method for shape model fitting. The results can be seen in Figure 2 f). To perform the fine alignment, the parametric non rigid registration algorithm is used. For initial parametrization, the output of the rough alignment is used. The algorithm iteratively minimizes the distance between the target and the shape model mesh. In a last step, the grasp points are determined on the target mesh. They can be automatically derived as they are defined on the shape model and were deformed accordingly in the fitting process.

3 Results

The results of the fitting procedure and the grasp point determination are presented below.

For the shape model fitting we determined the following metrics: the average distance (in mm), the Hausdorff distance (in mm), and the processing time (in seconds). The average distance is the distance between defined landmarks of the shape model and target mesh, while the Hausdorff distance represents the distance of two set of points. Table 1 summarizes the results.

Average Distance (mm)	Hausdorff Distance (mm)	Time (sec)
	Artificial	
0.1±0.01	0.93±0.24	59.34±1.03
	Phantom	
0.33±0.25	7.78±7.71	60.16±1.06
	Ex-vivo	
0.72± 0.54	11.22±7.94	67.71±3.04

Tab. 1: Results of the parametric, non-rigid registration fitting, with 18 landmarks used.

We evaluated the fitting accuracy in all three scenarios. In all three scenarios we reach an average distance of under 1 mm. For the artificial and the phantom scenarios, the Hausdorff distance is 0.93±0.24 mm and 7.78±7.71 mm, respectively. For the ex-vivo scenario the Hausdorff distance is 11.22±7.94 mm. The processing time is 59.34±1.03 seconds (sec) for the artificial gallbladder, 60.16±1.06 sec for the phantom, and 67.71±3.04 sec for the ex-vivo organ.

The grasp point determination was evaluated by a medical expert for all three scenarios. He had the option to rate a detected grasp point as "good", "minor deviation", and "not usable". Grasp points rated as "minor deviation" are usable but may lead to unfavorable grasps.

Artificial: The shape model fitting was performed on 19 artificially created gallbladders. 90% of the determined grasp points were rated as "good", 8.33% as "minor deviation" and 1.67% as "not usable". *Phantom:* To evaluate the fitting to our phantom we used nine point cloud recordings. All determined grasp points were rated as "good". *Ex-vivo:* The fitting was performed on nine ex-vivo organs. 90% of the grasp points were determined as "good", 3.33% as "minor deviation", and 6.67% as "not usable".

An example of determined grasp points on a phantom is visualized in figure 1.

4 Discussion

There are many different possibilities to construct a statistical shape model. We used the approach of automatically generate a Point Distribution Model through variations of artificially generated gallbladders. Additionally, there are some parameters that can be altered to fine tune the shape model.

In our result section we present the best fitting results based on the distance metrics. One limitation, when working with statistical shape models is often the time needed to perform a fitting. To reach the highest fitting accuracy our approach needs approximately one minute to fit the shape model to a scene. However, we tested different parameter combinations and evaluated the distance metrics and processing time. For lower average distance values of 2-4 mm, the processing time is faster.

In our scenario this would still be sufficient, while in other scenarios, e.g. neurosurgical scenarios, the approach needs to be as accurate as possible. It is planned to examine various fitting algorithms in the future that enable faster fitting and at the same time provide accurate fitting results.

We have defined three grasp points on the gallbladder, reflecting most used grasp areas during the removal of the gallbladder. The exact definition of the correct position of a grasping point is difficult and can be debated. The presented results need to be interpreted in this context.

5 Conclusion

In this work, we have presented a statistical shape model for the determination of grasp points on the gallbladder for different scenarios. We were able to find at least in 90% of cases valid grasp points even in difficult deformation states on ex-vivo organs. We reach an average distance of the fitting of under 1 mm.

Future work will investigate how the fitting step can be optimized to minimize the process time. Additionally, further usage possibilities of the shape model will be investigated, e.g. as a digital twin.

Author Statement

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