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Does the 3D Feature Descriptor Impact The Registration Accuracy in Laparoscopic Liver Surgery?

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Abstract: In laparoscopic liver surgery (LLS) image-guided navigation systems could support the surgeon by providing subsurface information such as the positions of tumors and vessels. For this purpose, one option is to perform a registration of preoperative 3D data and 3D surface patches reconstructed from laparoscopic images. Part of an automatic 3D registration pipeline is the feature description, which takes into account various geometric and spatial information. Since there is no leading feature descriptor in the field of LLS, two feature descriptors are compared in this paper: The Fast Point Feature Histogram (FPFH) and Triple Orthogonal Local Depth Images (TOLDI). To evaluate their performance, three perturbations were induced: varying surface patch sizes, spatial displacement, and Gaussian deformation. Registration was performed using the RANSAC algorithm. FPFH outperformed TOLDI for small surface patches and in case of Gaussian deformations in terms of registration accuracy. In contrast, TOLDI showed lower registration errors for patches with spatial displacement. While developing a 3D-3D registration pipeline, the choice of the feature descriptor is of importance, consequently a careful choice suitable for the application in LLS is necessary.

Keywords: Laparoscopic liver surgery, 3D-3D registration, 3D local feature descriptors

1 Introduction

Laparoscopic liver surgery (LLS) has many benefits for the patients e.g. less pain and shorter hospital stays compared with open surgery. However, it needs a trained surgeon to cope with several challenges, e.g., no haptic feedback and a limited field of view. An image-guided navigation system during the surgery could further support the clinician by showing subsurface structures, e.g. hepatic vessels and tumors. Guidance information can be obtained from preoperative Computer Tomography (CT) or Magnetic Resonance Imaging (MRI) scans that can subsequently be reconstructed to a 3D model. The 3D model can then be used overlayed onto the laparoscopic video image to provide additional anatomical information. For the computation of the overlay, one option would be the 3D reconstruction of the laparoscopic image data using for example a stereo laparoscope. In general, the needed 3D global registration pipeline can be divided into three main steps. First, landmarks have to be detected. Landmarks are characteristic points (in this case in the 3D space) which can be robustly recognized in the registration process. In a second step, these landmarks have to be described. The feature description should ensure an unambiguous representation of the landmarks. Thus, in a last step, corresponding landmarks of the two data sets can be found and matched.

Robu et al. introduced a registration pipeline for LLS using the Triple Orthogonal Local Depth Images (TOLDI) feature descriptor and the Random Sample Consensus (RANSAC) matching algorithm [1]. They proposed a pruning step between the feature description and the feature matching step to select an optimal set of landmarks. However, in case of small surface patches (less than 20% of the whole liver surface) the registration accuracy was limited. Pfeiffer et al. proposed to solve the registration problem with a convolutional neural network which does both, finding correspondences and non-rigidly matching both point sets [2]. However, in advance a manual coarse registration step had to be performed. Recently, Koo et al. published an automatic 2D-3D registration approach using a semantic liver contour detection [3]. Their deep learning based contour detection performed robustly. Nevertheless, the registration itself only worked accurately with a visible surface of at least 30%. Thus, due to several challenges the registration problem in LLS is not solved yet.

Beside the mentioned TOLDI algorithm, in the last years different 3D local feature descriptors were published [4]. However, they were not designed with an application focus on LLS. Several papers compare their descriptiveness on specific 3D data sets from a retrieval or laser scanner [5]. The used data have in common to show distinct structures like edges, strong curvatures, etc. However, in LLS, only a few characteristic structures exist due to the smooth shape of the liver.

In this work, we state the following hypothesis: The feature descriptor impacts the accuracy of the registration pipeline.

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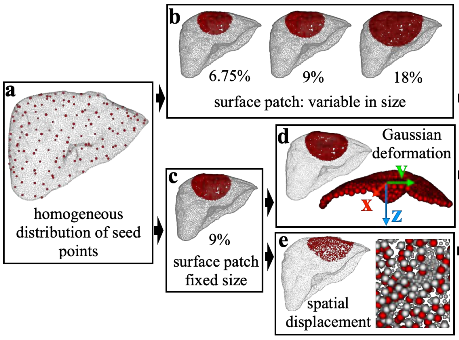

Fig. 1: Data generation as used for the three experiments. From left to right: First, seed points were homogeneously distributed. Second, either the surface patch was varied or a fixed patch size of 9% was modified by adding spatial displacement or Gaussian deformation. Third, the patch was transformed.

There is room for improvement to facilitate the development of a robust and accurate registration pipeline for LLS. For better understanding the importance of the feature descriptor choice we compare two feature descriptors: The TOLDI and the Fast Point Feature Histogram (FPFH) descriptors [6, 7]. Thereby, we include different disturbances observed in the data from LLS.

2 Materials and Methods

The point set of a liver phantom from the OpenCAS dataset [8] was used as input for the evaluation of feature descriptors. As depicted in Fig. 1, patches were extracted from the complete point set (in the following referred to as "surface patch"). The surface patches were used as a surrogate for the intraoperative point set that may be reconstructed by a stereo laparoscope. The original, complete and not modified point set serves as a surrogate for a preoperative point set acquired with a scanning modality device (e.g. CT or MRI). This simulation setting facilitates the assessment of the impact of different confounding factors on the accuracy of the registration of the (intraoperative) surface patch with the (preoperative) point set.

Surface Patch Size: The intraoperative working distance determines the size of the surface patch that can be reconstructed. Surface patches of varying size were extracted from the complete point set (Fig. 1 b). To this end, on the whole point set a certain number of seed points were homogeneously picked (Fig. 1 a). Each seed point serves as the center point for a surface patch. A nearest neighbor approach was applied to identify surrounding points that subsequently form a surface patch of a given size around the seed point.

Spatial Displacement: Spatial displacement was applied to the surface patch to simulate different point grid sampling scenarios that may occur in a real-world scenario e.g. due to the multi-modality and noise of the laparoscopic data. Therefore, a uniformly distributed spatial offset in x-, y-, and z-direction was applied to each point of the surface patch (Fig. 1 e).

Gaussian deformation: Gaussian deformation with a varying amplitude was applied to the surface patch to mimic deformation relative to the preoperative complete point set as it appears in LLS due to the insufflation pressure (Fig. 1 d).

2.1 Registration Pipeline

The encoding of local information in a point set is important for point set registration. This is especially the case when a surface patch needs to be registered to its corresponding location on a larger point set. In this case, the descriptiveness of the locally encoded information is of utmost importance to guide the registration process. Two histogram-based feature descriptors were exemplarily evaluated in this study, namely TOLDI and FPFH. A reason for the choice is the different working principle. The TOLDI generates a local reference frame and calculates local depth information, thus it encodes geometric and spatial information of the surface. Whereas, the FPFH focuses on geometric information as it uses surface normals for the feature description. For further information regarding the working principle of the feature descriptors we refer to the original papers [6, 7]. For the FPFH descriptor, all points were used for the feature description. The TOLDI descriptor receives again all points on the surface patch. The set of landmarks on the whole geometry consisted in our case of 1000 homogeneously distributed points from the whole surface. The number was chosen according to [6]. We distributed the points in the set homogeneously to guarantee the availability of a correspondence set. For both feature descriptor, the default settings as proposed in the original papers were used. The RANSAC with default settings was used for feature matching as implemented in the Open3D package [9, 10].

2.2 Experiments

Surface patches covering the complete point set were generated. For both feature descriptors, the registration of each individual surface patch with the complete point set was repeated 30 times. Three experiments were derived from this setting:

1. Impact of surface patch size (Fig. 1: a - b - f): The experiment was conducted with surface patch sizes ranging from 6.75% to 18% in increments of 25%. No disturbances were applied to the surface patches.
2. Impact of spatial displacement (Fig. 1: a - c - e - f): The experiment was conducted with a constant surface patch size of 9%. Spatial displacement was applied to each surface patch with a magnitude ranging from 0.5 mm to 2 mm.
3. Impact of deformation (Fig. 1: a - c - d - f): The experiment was conducted with a constant surface patch size of 9%. Gaussian deformation with an amplitude ranging from 5 mm to 30 mm was applied to each of the surface patches.

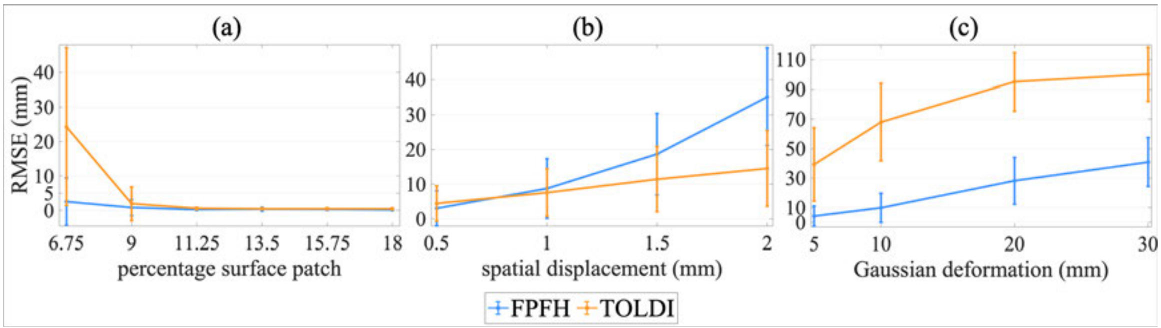

Fig. 2: RMSE (Mean and std) for different surface patch sizes (left), spatial displacement (middle) and Gaussian deformation (right).

The Root Mean Square Error (RMSE) was used to assess the registration accuracy. Since a rigid matching was performed, the optimal registration result (RMSE = 0 mm) was defined as a complete compensation of the rotation and translation but not of the disparity (spatial displacement or deformation) between both point sets.

3 Results

Impact of Surface Patch Size: Fig. 2(a) shows the averaged RMSE calculated over all surface patches, which was substantially lower for FPFH compared to TOLDI for surface patches of size 6.75% (mean±standard deviation (std) = 2.6 mm±6.9 mm and 24.3 mm±22.8 mm, for FPFH and TOLDI, respectively). No substantial difference regarding the averaged RMSE was found for surface patch sizes of at least 11.25% and larger between FPFH and TOLDI.

Impact of Spatial Displacement: Both feature descriptors are affected by spatial displacement. Nevertheless, FPFH was found to be more sensitive to spatial displacement at an amount of 1 mm and higher compared to TOLDI as indicated by a substantially higher RMSE on average. The results are illustrated in Fig. 2(b).

Impact of Gaussian Deformation: The averaged RMSE calculated over all surface patches at different locations on the complete point set was substantially lower for FPFH compared to TOLDI for all amplitudes of deformation. The results are illustrated in Fig. 2(c).

Impact of Location: In Fig. 3, the RMSE distribution of the anterior side of the liver model is depicted for three different cases: "normal" (no modification of the surface patch), spatial displacement of 1 mm, and Gaussian deformation of 10 mm. The surface patch size was set to 9%. The color distribution covers the interquartile range for each case. For the FPFH, patches on the anterior ridge have generally higher RMSE values (especially for spatial displacement). For TOLDI, the patches with higher RMSE values are rather located on the right liver lobe. The distribution is similar for all three cases.

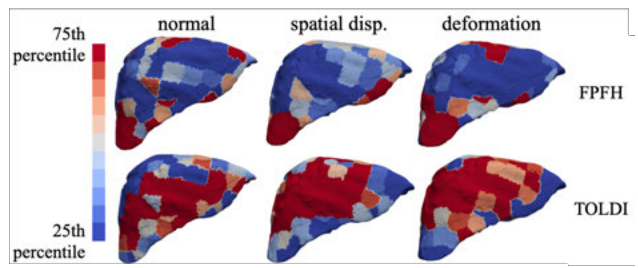

Fig. 3: RMSE distribution on the anterior side of the liver for three cases: normal (no modifications), spatial displacement (disp.) of 1 mm and deformation of amplitude 10 mm for FPFH and TOLDI. The surface patch size was set to 9%.

4 Discussion

The purpose of this study was to assess the impact of two different feature descriptors on the registration performance. Thereby, a simulated setting, which allows to control different impact factors that may occur in LLS, was used. The results demonstrated that the FPFH descriptor provided more accurate overall registration results compared to the TOLDI descriptor for small surface patch sizes reflecting 6.75% of the complete point set. A possible explanation for the inferior performance of the TOLDI descriptor for small surface patches could be an instability with respect to the establishment of the used local reference frame. The FPFH calculation only relies on the surface normales of a small neighborhood. For surface patches reflecting 11.25% of the whole surface and larger, both options were able to match both points sets very accurate (less than 1 mm mean RMSE). For the ideal case, a registration of a surface patch with the preoperative 3D CT/MRI model in LLS is possible assuming a realistic patch size of approximately 9%. TOLDI features were found to be more robust against spatial displacement compared to FPFH features. The robustness of TOLDI was also evaluated and found to be high in a review paper [5] and was the reason for Robu et al. to choose it as an appropriate feature descriptor [1]. Moreover, this result is in accordance with the theoretical considerations, since the FPFH feature descriptor uses normals which are especially disturbed when adding spatial displacement. Otherwise, spatial displacement seems to not disturb the local depth images, which are used by TOLDI, much. The result obtained with deformed surface patches were contrary. The FPFH option showed more robust registration results compared to TOLDI. An explanation could be the feature characteristics used by TOLDI. It uses depth information from three different perspectives. However, due to the deformation, the depth of the patches is also changed and yields therefore a weak foundation for the matching process. The RMSE values on the liver surface were different distributed for FPFH and TOLDI. The higher RMSE values for TOLDI in flat regions is consistent to the findings by dos Santos et al. [11]. For flat surface patches, which especially occur on the right liver lobe, the registration problem can be ambiguous. For the FPFH case, RMSE values for flat patches were generally lower than with TOLDI. This could support the theory of a higher descriptiveness in these areas. For spatial displacement, the FPFH features seem to be more ambigious for patches at the anterior ridge than TOLDI features. This might be connected to the fact that in patches with a higher curvature, spatial displacement affects the structure. Thus the point's normals change more than if patches are flat and FPFH features are less reliable.

The histogram, which is the feature vector, generated with the TOLDI has a length of 1200 bins in contrast to 33 bins for the FPFH descriptor. Thus, the computation time for the TOLDI itself, as well as for the matching, is much higher. We decided to use 1000 landmarks on the whole surface as proposed in [6], and all points on the patch to guarantee the existence of correspondences. For the FPFH calculation, however, all points were used as landmarks. Thus, the initial situation regarding the landmarks is not equal. This has to be further evaluated, nevertheless, considering all points as landmarks for TOLDI would lead to an ernourmous increase in computation time. Even when using only 1000 points for TOLDI the computation time was at least 10 times higher as for FPFH (e.g. for the non-modifed case and a surface patch size of 9%: 0.7 s for FPFH in contrast to 8.6 s for TOLDI). Taking the demand for a real-time solution into account, it is questionable if this is at all practicable.

There are several limitations of this study. First, the proposed registration framework provides a simplified setting with respect to the real-world setting of LLS, e.g. only one type of deformation (Gaussian) was considered. Stereoscopic surface reconstruction provides its own challenges and sources of errors, e.g. light reflections on the laparoscopic video, that may lead to inaccurate surface reconstruction results. Moreover, the matching problem could be restricted to the anterior side of the liver since the posterior side is not visible in a real-world setting. Second, the results shown in this study are only obtained from a single point set from a liver phantom of the OpenCAS dataset. Therefore, it would be interesting to confirm the results on real-life point sets derived from CT and/or MRI scans of real patients. Finally, an adjustment of the used parameters, e.g. the support radius, could impact the registration accuracy.

5 Conclusion

The feature descriptor is an integral part of the registration pipeline and the selection of an appropriate feature descriptor is crucial to achieve a reasonable registration accuracy in a LLS setting. In future, additional feature descriptors should be compared. Furthermore, a feature descriptor optimized for the registration of a preoperative 3D liver model and an intraoperative surface patch should be developed.

Author Statement

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