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Quantitative evaluation of camera-based 3D reconstruction in laparoscopy: A Review

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Abstract: The quantitative evaluation of 3D reconstruction methods might support the successful improvement and extension of computer assisted surgery in regard of applications as augmented reality and (autonomous) robot-assisted interventions. There is a selection of around eleven evaluation metrics from which the root mean squared error, the mean absolute error and the standard deviation are the most used. For this work a literature review was done with the objective to give a statement about promising 3D reconstruction methods regarding accuracy. Therefore, quantitative evaluation results of 44 articles from 2015 to 2022 were analysed. The review includes the reconstruction methods stereoscopy, Shape-from-Motion, Shape-from-Shading, Simultaneous Localization and Mapping, artificial intelligence-based approaches (machine-learning), structured light, multicamera and trinocular approaches and the so-called Smart Trocar®. It can be identified that machine-learning approaches in combination with stereo images and stereoscopy in combination with structured light deliver the best results with values in submillimetre range, thus seem to be promising for future research.

Keywords: 3D reconstruction, Laparoscopy, Quantitative Evaluation, Review

1. INTRODUCTION

Laparoscopy has been a big step to enable minimally invasive surgery (MIS) which leads to a reduced patience´s healing duration and less surgical trauma (Jaffray, 2005). State-of-the art laparoscopes contain either a mono or a stereo camera system, while second is the more advanced system due to the generation of stereo images. With this, surgeons perceive depth and can perform faster (Vettoretto et al., 2018). A next development step is 3D surface reconstruction of the abdomen based on laparoscopic images. This would provide information about surface structure, colours and distances, which makes it useful for documentation (Leibetseder et al., 2020), diagnosis (Wu et al., 2022), image guided surgery (augmented reality (AR)) (Andrea et al., 2018) and (autonomous) robot-assisted interventions (Saeidi et al., 2022).

There are nine different camera-based methods for 3D reconstruction in laparoscopy which could be found in the literature: Structure-from-Motion (SfM), Shape-from-Shading (SfS), stereo vision, trinocular or multicamera approaches, Simultaneous Localization and Mapping (SLAM), structured light (SL), deep-learning (artificial intelligence) approaches (AI), Time-of-Flight (ToF) cameras and the so-called Smart Trocar®.

3D reconstruction requires 3D point clouds, which are generated by camera-based depth estimation. Most techniques estimate depth by applying triangulation. In case of stereo vision, triangulation is calculated between the two cameras and the object. In case of SfM, it is calculated between two (consecutive) image frames, which are taken during monocular camera movement, and the object. In case of SL mono, it is calculated between the monocular camera, the projector, and the object. In contrast to that, SL stereo is comparable to stereo vision. The other methods are different. SfS depth estimation is based on light intensities. ToF is based on the duration of laser reflection. AI approaches are based on machine learning. SLAM estimates the camera´s poses based on features and maps at the same time.

3D reconstruction is challenged by the conditions within the human body and image artifacts talking about light reflections, organ specularity, tissue movements, few contrasts, blur, unprecise camera positioning and missing fixed landmarks (Göbel & Möller, 2022). Besides this, strict requirements are demanded such as a high accuracy (submillimetre range), high robustness, real-time computing, high image resolution, dense 3D point clouds and ideally no additional hardware (Göbel & Möller, 2022).

The question is how a laparoscopic system could be designed and which algorithms would be suitable to fulfil these high demands. Which 3D reconstruction technique should be best used in laparoscopy to deliver high accuracy? To probably answer these questions, this paper offers a review about 3D reconstruction in laparoscopy over the last eight years and

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focuses on the quantitative evaluation of reconstructed surfaces.

2. METHODS

For literature search the engines “google scholar” and “PubMed” were used with the keywords “3D reconstruction”, “three-dimensional reconstruction”, “surface reconstruction” in combination with “laparoscopy”, “endoscopy”, “comparative study”, “review” and “survey”. The filter “year of publication” was set from 2015 to 2022 to exclusively discuss research from the eight years. Exclusion criteria were general endoscopy (except laparoscopy), not camera-based 3D reconstruction techniques and the absence of quantitative analysis (see Figure 1). With the above-mentioned keywords 664 papers were found which needed to be filtered by reading abstract and keywords. 321 papers were rejected due to not being about laparoscopy and 199 more because they were not about camera-based 3D reconstruction, but about MRT or CT. This results in 67 papers. The last criterion was the presence of quantitative evaluation of reconstruction results. Only papers which include the reconstruction error (error between real and reconstructed surface) were considered. Papers computing the registration error (registration between CT/MRT model and laparoscopic image) were excluded. In the end 44 papers have been declared as relevant and were considered in this paper. This review contains studies on 3D reconstruction in laparoscopy from full text articles, conference-proceedings and -abstracts. Articles published until December 31st, 2022, were picked.

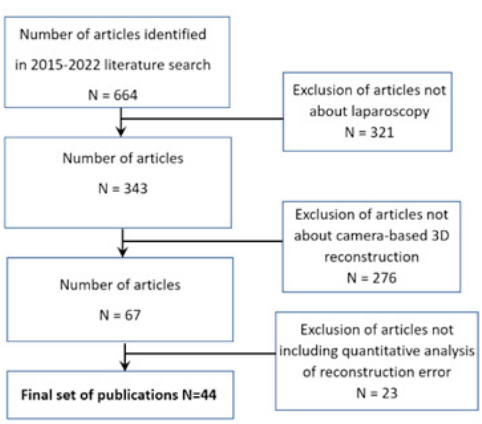

Fig. 1. Paper exclusion tree.

There are different ways for the quantitative evaluation of a reconstructed surface, but all require the presence of ground truth of the reference model. Most authors talk about accuracy which can also be called reprojection error and is described as Euclidean distance between each reconstructed surface point and its corresponding closest point on the real surface. The distance can be computed as mean absolute error (MAE), magnitude of relative error (MRE), standard deviation (STD), root mean squared error (RMSE), root mean squared logarithmic error (RMSE log), absolute error (AbsRel) and squared error (SqRel). Most authors only compute MAE and RMSE, thus these two metrics will be analysed in this study.

3. RESULTS

The objective of this work is to analyse which reconstruction technique delivers the highest accuracy. This chapter presents the review´s results. Table 1 shows the distribution of 3D reconstruction techniques which were applied in a paper within the years 2015 – 2022 (all 67 papers were considered besides the quantitative analysis, one paper applied two methos resulting in the total of 68). It can be observed that stereoscopy and AI approaches were used the most. The best years for SfM, SfS, stereoscopy and SL were before 2019, whereas AI approaches became more and more popular beginning with 2019. Smart Trocar®, trinocular und multicamera approaches were rare and ToF was not used at all.

Table 1. Overview of 3D reconstruction techniques in laparoscopy from 2015 - 2022

3D reconstruction technique	2015	2016	2017	2018	2019	2020	2021	2022	Total
AI		1		1	2	1	5	6	16
Multicamera					1				1
SfM	1	1	5	1	1	1			10
SfS	1								1
SLAM			2	2	1	2	1		8
SL	2	1	2	3	1	1		1	11
Smart Trocar®			1						1
Stereoscopy	4	2	3	6		3		1	19
Trinocular			1						1
Total	8	5	14	13	6	8	6	8	68

Of all 44 papers, we could find 29 MAE values and 28 RMSE values, which are visualized in relation to the 3D reconstruction method in Figure 2. The authors of the trinocular approach did not provide a MAE or RMSE value, which is why it is missing in the graph. The data including all the references are provided in the table in Appendix A.

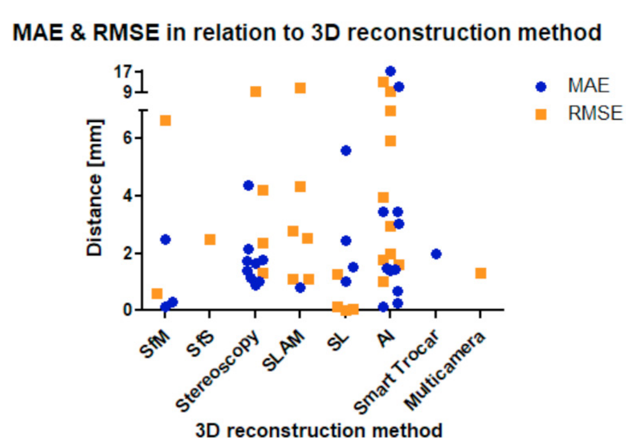

Fig. 2. Visualization of MAE and RMSE values in relation to the 3D reconstruction method.

Five key findings could be concluded from this graph:

1. MAE and RMSE values lie in a similar range.

2. Both values show high variations.
3. Lowest RMSE value at 0.0078 mm (SL).
4. Lowest MAE value at 0.12 mm (AI) and 0.15 mm (SfM).
5. Only 12% of papers could reach submillimetre accuracy

4. DISCUSSION

In this chapter the five key findings and additional aspects are discussed.

1) MAE and RMSE values lie in a similar range. The expectation on that was that the MAE values would be lower than the RMSE values because outliers weigh more in RMSE. In this case MAE and RMSE confirm the same thing: Both values have high variations and only a few papers could reach submillimetre accuracy.

2) MAE and RMSE values show high variations. First, it must be mentioned that the amount of data is low – especially when looking at SfM, SfS, SLAM, SL, Smart Trocar® and multicamera systems. For a clear statement more data are needed. But even when there are more data – as for AI approaches – the variation reaches from 0.12 mm to 17.42 mm. To find an explanation, the authors plan a deeper analysis in the next paper. We assume influence factors as the reference object for the quantitative analysis, the acquisition of ground truth, the method of camera localization, the number of images or datasets and the image resolution.

3) Lowest RMSE value at 0.0078 mm (SL). The usage of structured light exists for many decades and is already applied in industrial measurement devices. The additional light source creates features on the surface, which leads to additional information usable to find corresponding points. Thus, the high accuracy of SL approaches was expected. On the other hand, it needs to be highlighted that (Sui et al., 2018, 2019a) only used basic geometric objects (plate, cylinder) as reference objects, which reduces the level of difficulty and might explain the extremely high accuracy values of 0.0078 mm and 0.1285 mm (Sui et al., 2019a). In comparison to that, the SL approach in (Geurten et al., 2018) resulted in 1.28 mm RMSE, when taking an ex-vivo liver and kidney. The recommendation is that future research considers ex-/in-vivo organs or datasets for validation.

4) Lowest MAE value at 0.12 mm (AI) and 0.15 mm (SfM). Regarding the SfM approaches, we expected (Su et al., 2018) to outperform (Cheema et al., 2019) due to the known camera position, but the opposite can be seen. Ref. (Cheema et al., 2019) generated an accuracy of 0.15 mm, while (Su et al., 2018) only 6.6 mm. An explanation might be that in (Su et al., 2018) tools are present which occlude parts of the images and might lead to a more advanced situation. Moreover, (Cheema et al., 2019) used an additional template for reconstruction as well as shading cues to tune it, which surely improved the results.

Regarding the AI approach, the MAE value of 0.12 mm could not be confirmed by the corresponding RMSE value, which is 9.27 mm. This underlines the importance of measuring both the MAE and RMSE to get a complete validation.

5) Requirement of submillimetre accuracy cannot not be fulfilled by state of technology (88 % of articles have accuracy (RMSE) larger than 1 mm). The question is if submillimetre accuracy can be reached and especially under real conditions during laparoscopy including all challenges as movement (heartbeat, breathing, intestinal peristalsis), organ specularity, occlusions (instruments, blood, smoke) and more. So far, only under laboratory conditions with geometric objects as reference this requirement can be reached. The next question is if submillimetre accuracy is really required. Depending on the application the requirements might vary. For autonomous robot-assisted interventions it should be that high, whereas the supervision of CT images with laparoscopic images probably needs less accuracy if the laparoscope is guided manually.

6) Other aspects to consider for the validation of the reconstruction techniques. As mentioned in the second key finding, the variation of the reconstruction error is high. Explanations might be found in the different validation scenarios. For example (Shibata et al., 2018) used a phantom model for validation, whereas (Chen, 2019) took a simulated MIS scene and others validated their results on real laparoscopic image sequences, e.g. SCARED (Allan et al., 2021). For comparison purposes, a standard validation scenario must be defined:

- use publicly available datasets (SCARED)
- use porcine ex-vivo organs (liver) and generate ground truth with CT or 3D scanner
- measure the RMSE of the reconstruction error

Other criteria for the validation of the 3D reconstruction methods are the necessity of additional hardware, the computation time – especially real-time, the investment costs, and the compatibility with standard equipment, which most surgeons have. When looking at additional hardware, the techniques SfM, SfS, SLAM and AI approaches do not need it and thus, are also compatible with the standard equipment of most surgeons and clinics. The investment costs are lower than those techniques, which require additional hardware, e.g., SL, ToF and stereo vision. Real time computing is possible when using the GPU – especially for AI approaches.

5. CONCLUSION

This work reviewed research articles about 3D reconstruction and its accuracy in laparoscopy. It analysed which accuracy could be achieved by which 3D reconstruction method to give a statement about the most promising technique for future research. Most promising techniques are SL stereo, AI stereo and a template based SfM approach, which could deliver lowest values for MAE and RMSE, partly in submillimetre range.

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Appendix A. Data Table including MAE and RMSE

3D reconstruction method	MAE ± STD [mm]	RMSE ± STD [mm]	Author
SfM	-	0.6	(Cheema et al., 2019)
SfM	0.3-1.0	-	(Marcinczak et al., 2015)
SfM	0.15 ± 0.05	-	(Modrzejewski et al., 2020)
SfM	2.5-3.5	-	(Puig & Daniilidis, 2016)
SfM	-	6.628 vs. 8.398	(Su et al., 2018)
SfS	-	1.0-4.0	(Kumar et al., 2015)
Stereoscopy	4.4 ± 0.8	-	(Andrea et al., 2018)
Stereoscopy	-	5.45 [Pixel]	(Allan et al., 2016)
Stereoscopy + SfS	1.14	-	(B. Lin, 2015)
Stereoscopy + SLAM	1.77-3.7	-	(B. Lin, 2015)
Stereoscopy	-	4.21 ± 0.63	(Reichard et al., 2015)
Stereoscopy	1.75	-	(Penza et al., 2016)
Stereoscopy	1.0	-	(Kim et al., 2020)
Stereoscopy	-	9.35 ± 2.94	(Teatini et al., 2020)
Stereoscopy	1.4 ± 1.07	-	(Shibata et al., 2018)
Stereoscopy	0.89 ± 0.7	1.31 ± 0.98	(L. Zhang et al., 2017)
Stereoscopy	2.16 ± 0.65	-	(Wang et al., 2018)
Stereoscopy	1.65 ± 1.41	-	(Speers et al., 2018)
Stereoscopy + SLAM	-	2.37	(Chen, 2019)
SLAM mono	-	10.78	(Su et al., 2018)
SLAM stereo	0.8-2.2 ± 0.4-0.7	1.1-1.3* ± 0.6-0.7*	(Zhou & Jayender, 2021)
SLAM mono	-	4.32	(Chen et al., 2017)
SLAM mono	-	2.8	(Mahmoud et al., 2017)
SLAM mono	-	2.54	(Chen, 2019)
SLAM mono	-	1.1	(Mahmoud et al., 2019)
SL stereo	-	0.07	(Sui et al., 2018)
SL stereo	2.44 ± 0.34	-	(Le et al., 2018)
SL stereo	5.6 ± 4.9	-	(Edgcumbe et al., 2015)
SL mono	1.5 ± 0.6	-	(Edgcumbe et al., 2015)
SL mono	-	1.28	(Geurten et al., 2018)
SL mono	1.0 ± 0.4	-	(Fusaglia et al., 2016)
SL stereo	-	0.0078 0.1285	(Sui et al., 2019b)
AI mono	-	5.953	(Chen, 2019)
AI + SL mono + hyperspectral imaging	0.68 ± 0.13	-	(J. Lin et al., 2018)
AI stereo	3.44 3.47	7.01* (Rosenthal)	(Allan et al., 2021)
AI stereo	-	2.96	(Wei et al., 2022)
AI mono	0.26	1.98	(Chong, 2022)
AI mono	0.12	9.27	(Huang et al., 2022)
AI stereo	1.45 ± 0.4	1.62 ± 0.42	(G. Zhang et al., 2022)
AI stereo	3.05	3.961* ± 1.237*	(Luo et al., 2022)
AI stereo	11.23 17.42	-	(Huang et al., 2021)
AI stereo	1.41 ± 0.42	1.77 ± 0.51	(Luo et al., 2020)
AI stereo	1.49 ± 0.41	1.9 ± 0.38	(Luo et al., 2019)
AI stereo	-	13.18	(Antal, 2016)
Smart Trocar®	2.0	-	(Garbey et al., 2018)
Trinocular	± 1.1	-	(Conen et al., 2017)
Multicamera (10 cameras)	-	1.29	(Su et al., 2019)