

Dear Editor and **Reviewer 1**

Please find below responses and corrections summary for you remarks.

Major comments:

Comment:

In the related work section, the point cloud registration methods are presented in big detail in contrast to a brief description of the proposed method in section 3. For example, the HSNW (Hierarchical Navigable Small Worlds) algorithm that is proposed as the main difference in the proposed FIGRA pipeline is not presented in detail like the other algorithms in section 2, while one could argue it has a superior significance for the submitted paper.

Answer:

Thanks for your comments. We agree with the remark and we have added a more detail description of HNSW algorithm in separate subsection.

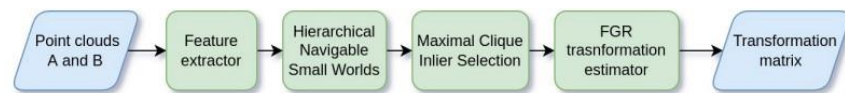


Figure 7. Flowchart of FIGRA modules.

3.1. Hierarchical Navigable Small Worlds

Hierarchical Navigable Small Worlds is a fully graph-based robust algorithm for approximate nearest neighbors (ANN) searches in vector space created by Yu. A. Malkova and D. A. Yashunin [33]. HNSW is the natural result of Navigable Small Worlds (NSW)

evolution. HSW is proximity graph with long-range and short-range links and (poly-)logarithmic complexity search. HNSW combines NSW and ideas hierarchical multi-layers from Pugh's probability skip list structure that creates performance with fast search speeds and high recall. There are later ANN graph searches, but among them, HNSW remains the most preferable in terms of the ratio of recall, building, and search time [34].

Minor comments:

Comment:

In Figure 3, there is no description for the EVD abbreviation.

Answer:

Thanks for the comment, clarification of EVD was added to the caption of the picture.

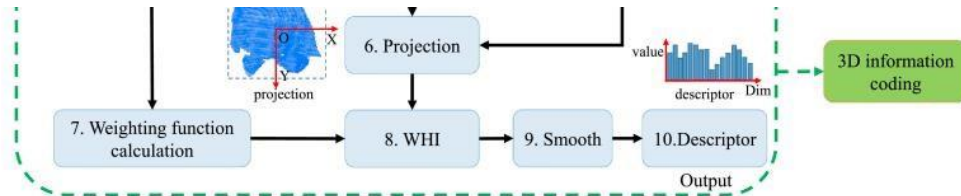


Figure 3. Flowchart of WHI descriptor calculation. EVD is an eigenvalue decomposition [19].

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Comment:

In section 5.2, it is mentioned that due to no ground truth information the evaluation is visual. Such a visual evaluation is largely subjective and the authors are encouraged to provide some clarification over this evaluation other than the Figure 9 that is provided.

Answer:

Thanks for your comments. We agree with the subjectivity of the visual assessment. A clarification of the visual evaluation has been added to the methodology section (5.1). The added clarification increases the objectivity of the visual evaluation.

subsection below. The effectiveness assessment consisted of the average registration time and the rate of successful alignments. No ground truth information exist about the actual transformation between pairs of point cloud origins. Thus, the alignment success for each pair was evaluated visually. Successful registration we considered the alignment of the planes of the room geometry in the area of overlapping point clouds, while the aligned planes are not visually separate planes, as shown in the example (Fig. 9). All algorithms were tested on Datasets A and B.

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Comment:

The Table 3 legend descriptions contain are hard to comprehend (e.g. the meaning of “more 90% cases ...”, “less 90% cases ...”) *Answer:*

You are right, it is not clear. Table 3 is needed to show algorithm performance with different feature descriptors and ICP iteration. In order to give a flexible evaluation, we add 90% range. Readers could use the result to choose the best configuration for their purpose. Our accuracy and runtime criteria are not absolute and for other cases it could be different. We have increased table caption and updated legend description on Table 3 to make it definitely.

Table 3. Results for FGR, Teaser++ and FIGRA on **synthetic dataset**. Table shows algorithms performance with different configurations, namely feature descriptors and ICP iterations.

Method	Feature	ICP	Feature radius (cm)						
			35	50	75	100	150	200	250
FGR	FPFH	-							
		1							
		10							
		100							
	WHI16	-							
		1							
		10							
		100							
	WHI36	-							
		1							
		10							
		100							
Teaser++	FPFH	-							
		1							
		10							
		100							
	WHI16	-							
		1							
		10							
		100							
	WHI36	-							
		1							
		10							
		100							
FIGRA	FPFH	-							
		1							
		10							
		100							
	WHI16	-							
		1							
		10							
		100							
	WHI36	-							
		1							
		10							
		100							

 : configurations with 100% results satisfied accuracy below 0.03 rad and 1 cm
 : configurations with more than 90% results satisfied accuracy below 0.03 rad and 1 cm
 : configurations with less than 90% results satisfied accuracy below 0.03 rad and 1 cm
 : configurations with 100% of execution runtime below 5 seconds
 : configurations with 100% of execution runtime below 10 second
 : configurations with less than 100% of execution runtime below 10 second

Comment:

While WHI (Weighted Height Image) descriptor is presented in the related work sections, WHI16 and WHI36 descriptors are mentioned in sections 5 and 6, with no clarification regarding the numbering. In addition, in the conclusion it is stated that “we tested a new WHI feature descriptor...”, while there is no mention of this in the rest of the manuscript.

Answer:

Sorry for the unclaring. 16 and 32 in WHI name mean the dimension of the descriptor. To eliminate ambiguity, an explanation has been added to the methodology section (5.1)

5.1. Efficiency evaluation of registration algorithms

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At the first stage, we evaluated the effectiveness of FIGRA and other four registration algorithms: Go-ICP, Bayesian-ICP, FGR, and Teaser++. FGR and Teaser++ were evaluated depending on Advanced Matching usage modes: On (use filtering correspondences) and Off (not use filtering correspondences). FGR, Teaser++, and FIGRA were also evaluated depending on different feature descriptors namely FPFH and WHI of two dimensions (16, 36), farther that will be named WHI16 and WHI36. The used feature radius did not exceed 150 cm, with the ratio close to the recommended, which is described in the

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