Bo LI, Yu ZHANG, Wen-jie ZHAO, Ping LI, 2020. Novel 3D point set registration method based on regionalized Gaussian process map reconstruction. *Frontiers of Information Technology & Electronic Engineering*, 21(5):760-776.
https://doi.org/10.1631/FITEE.1900457

Novel 3D point set registration method based on regionalized Gaussian process map reconstruction

Key words: Point set registration; Gaussian process; Intelligent unmanned system (IUS)

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Motivation

- To fulfill all of the complicated requirements, mobile intelligent unmanned systems (IUSs) rely heavily on accurate knowledge of their positions in the environment. When GPS is unavailable, estimating the ego-motion of IUSs using data from onboard sensors becomes a popular alternative solution. When point cloud data are used, this approach is known as point set registration.
- One taxonomy of point set registration applied to mobile IUSs can be generated: scan-to-scan registration and scan-to-map registration. Scan-to-scan registration methods can be fast but accumulate errors quickly; scan-to-map registration methods can limit the accumulation of errors to a great extent but operate with lower speeds because they require an extra process, i.e., map construction. Thus, there is interest in developing a registration method that possesses the advantages of both scan-to-scan and scan-to-map methods.
- The grid map, which is one of the most widely used laser-based map representations, has limitations and drawbacks. It is desirable to develop a kind of map representation that fully reveals the structure of the environment with low memory cost.

Main idea

- We use a Gaussian process (GP) to reconstruct the point cloud data. To deal with the problem that the entire region cannot be modeled with a single GP, a “divide and conquer” strategy is employed: we divide the entire region into small sub-regions, and the functional relationship for each sub-region is determined separately.
- Regarding the combination of test locations and predictions as predictive points can simplify the registration process significantly: point correspondence can be set up straightly by identifying the predictive points with the same test locations, and the rigid transformation can be analytically obtained using the singular value decomposition (SVD) method.
- The complexity of building a GP model is cubic. Thus, to ease the computational burden, a GP acceleration technique needs to be employed.

Method (regionalized GP map reconstruction)

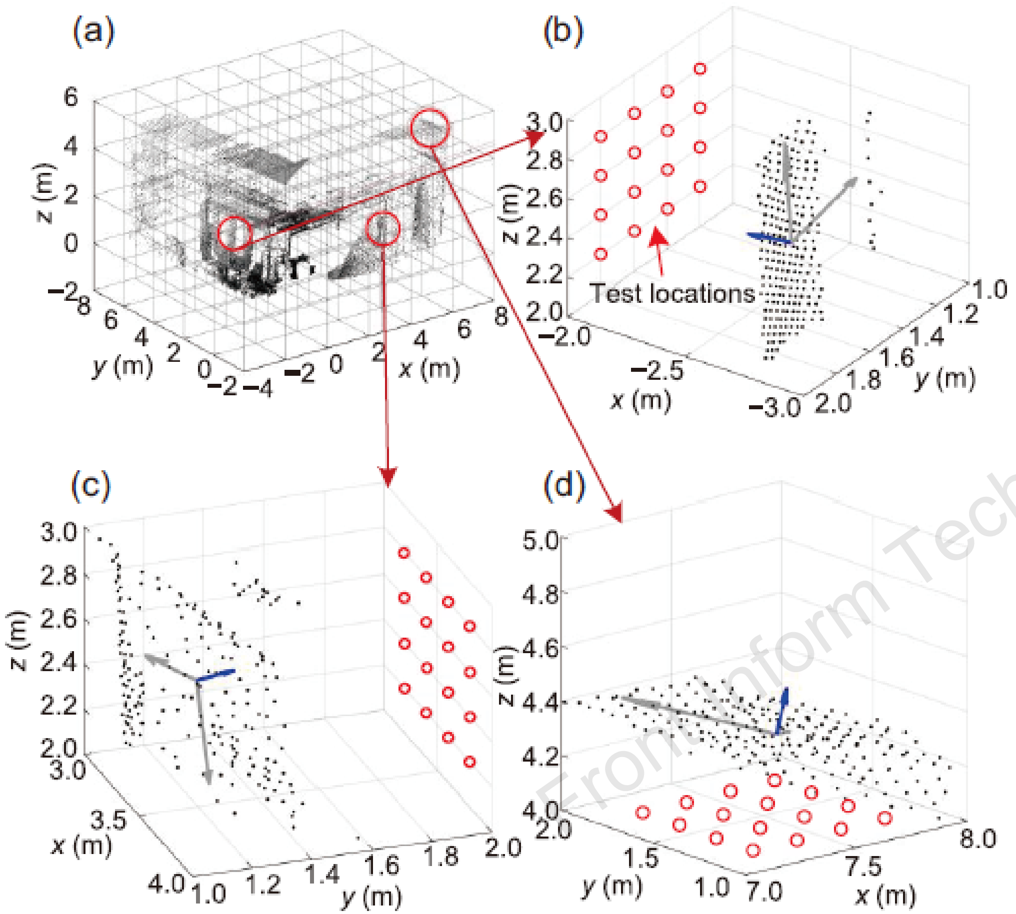

Fig. 1 Illustration of regionalization and the process for determining the functional relationship in sub-regions: (a) the entire raw point cloud; (b) a sub-region whose functional relationship is determined as *x*=*f*(*y*, *z*); (c) *y*=*f*(*x*, *z*); (d) *z*=*f*(*x*, *y*)

- Use principal component analysis (PCA) to find a normal direction (blue arrow) for each subset of points (black dots).
- To choose a proper relationship, the angles of the normal direction relative to the *x*, *y*, and *z* axes are calculated.
- Calculate the predictions at the selected test locations (red circles). The kd-tree based GP acceleration technique is applied.

Method (registration)

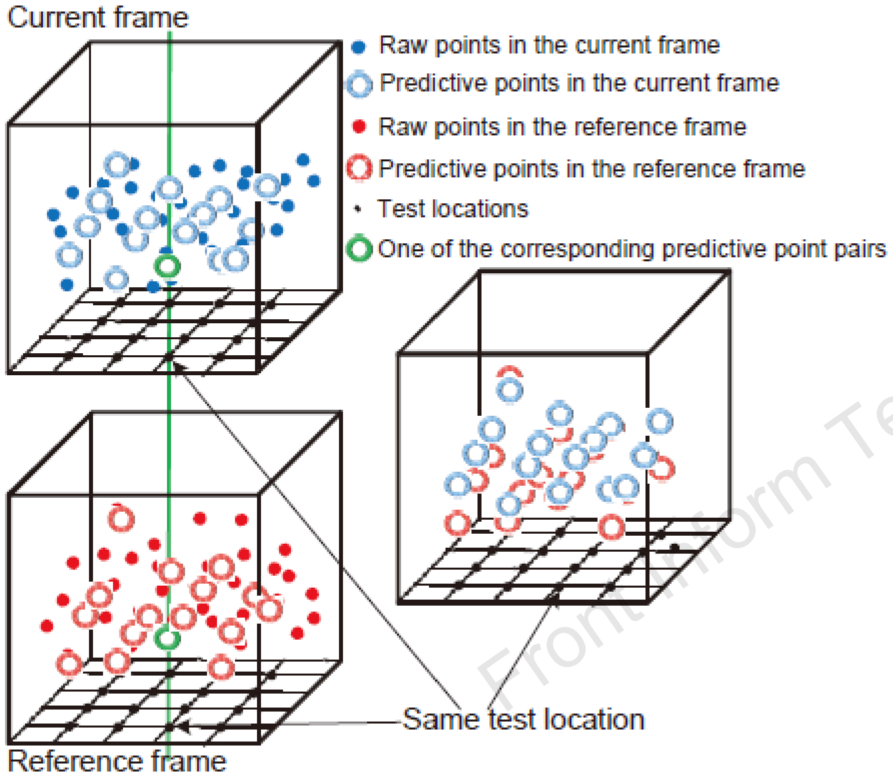

Fig. 3 Illustration of point correspondence construction

- The registration proceeds in an iterative manner.
- For each iteration, set up the correspondence between the predictive points by selecting points with the same test locations
- Use the SVD method to calculate the rigid transformation
- Set a proper termination condition.

Major results (data used)

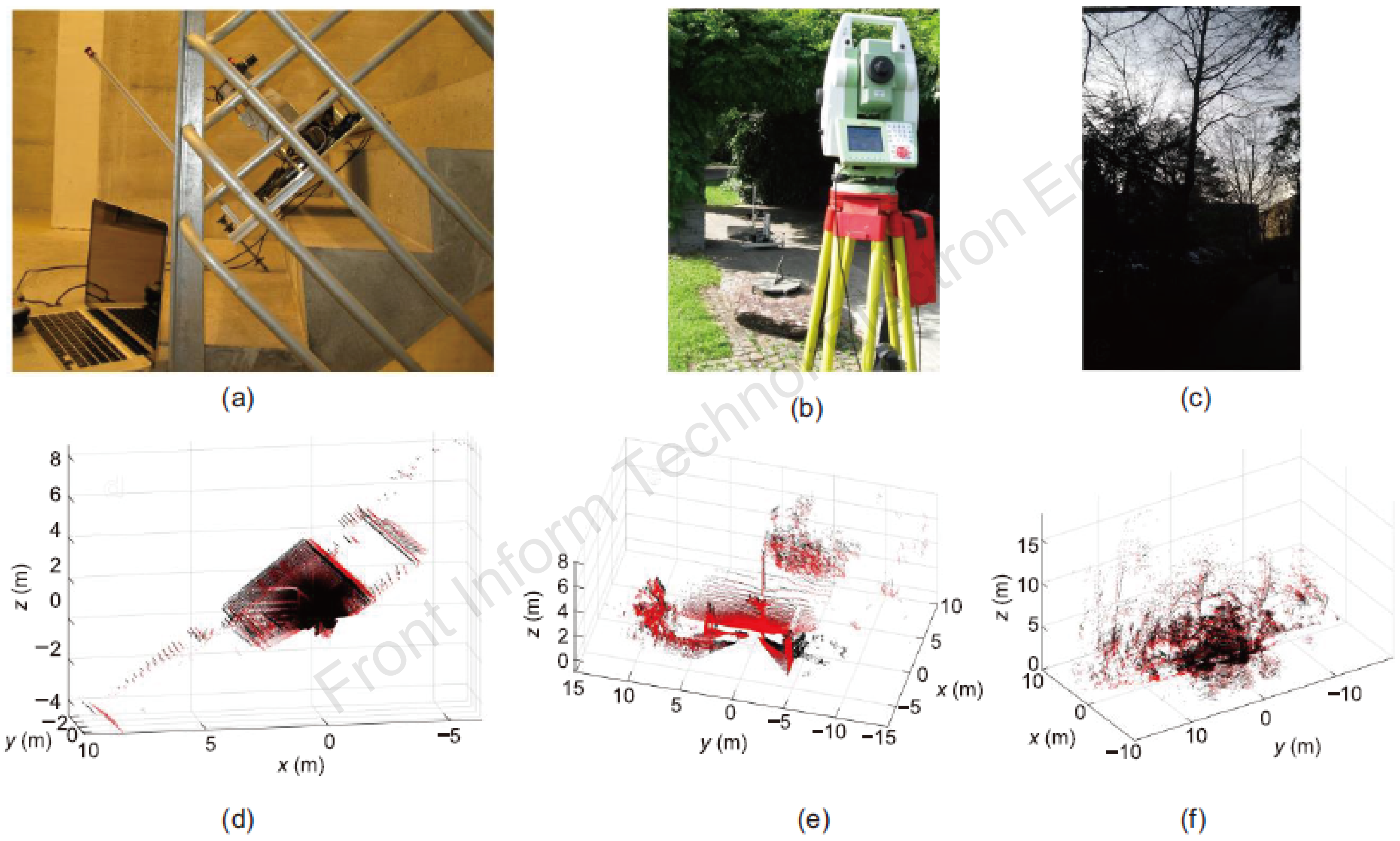

Fig. 4 Real-world views of the environments of the Stairs (a), Gazebo (b), and Wood (c) datasets, and point pairs from the Stairs (d), Gazebo (e), and Wood (f) datasets. (a)–(c) are directly downloaded from https://projects.asl.ethz.ch/datasets/doku.php?id=laserregistration:laserregistration. The black and red dots in (d)–(f) indicate the point cloud pair selected from each sub-dataset. References to color refer to the online version of this figure

Major results (mapping results)

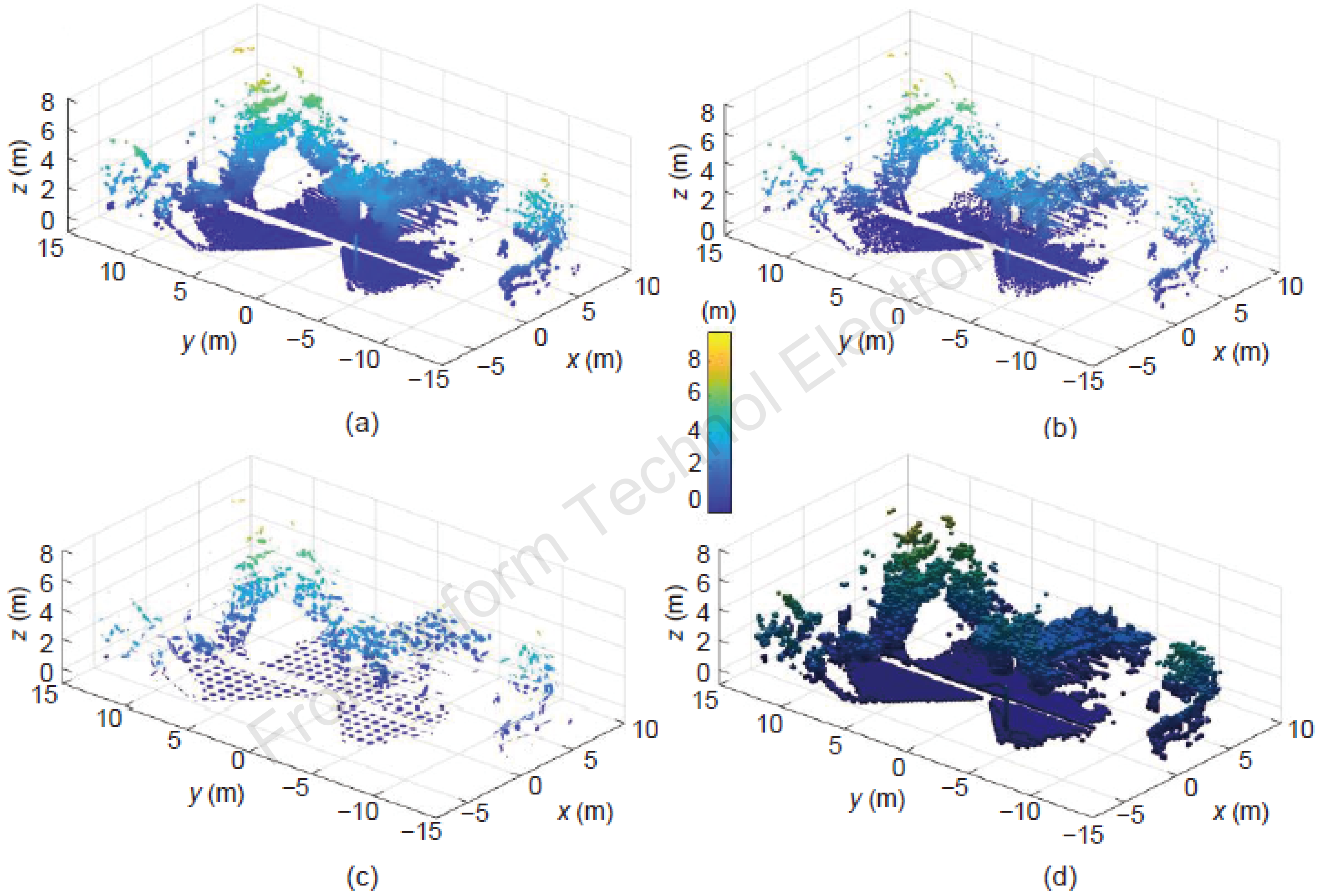

Fig. 5 Mapping results of the point cloud map (a), GP map (b), NDT map (c), and OctoMap (d). Colors indicate the height. The normal distribution in each cell including the mean value of the points and the covariance matrix of the points is visualized as ellipses. References to color refer to the online version of this figure

Major results (convergence)

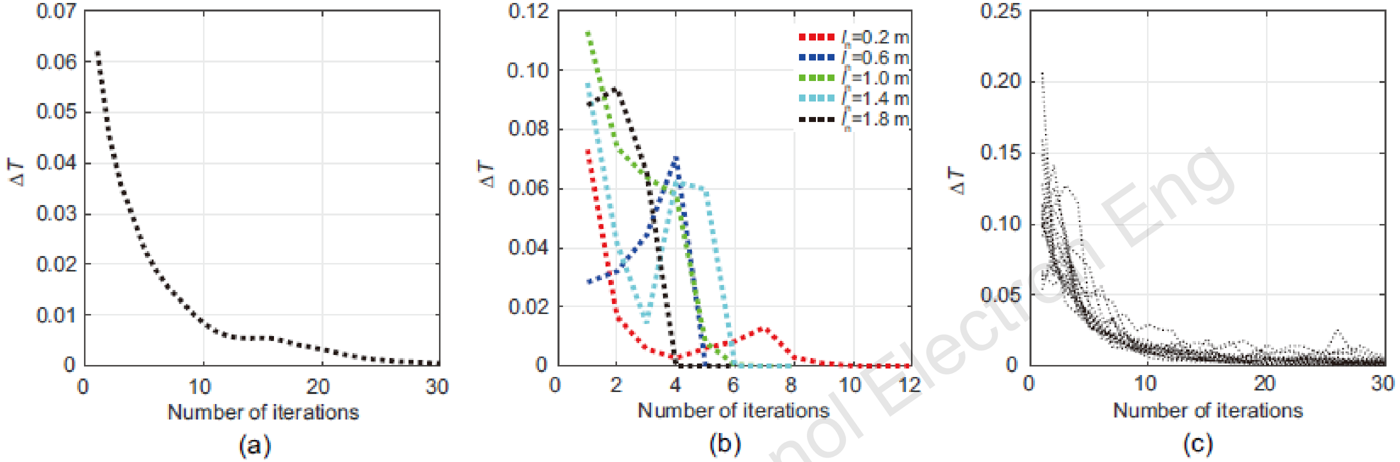

Fig. 6 Convergence results of experiment Stairs: (a) ICP; (b) NDT; (c) GP registration with different σ_t and l

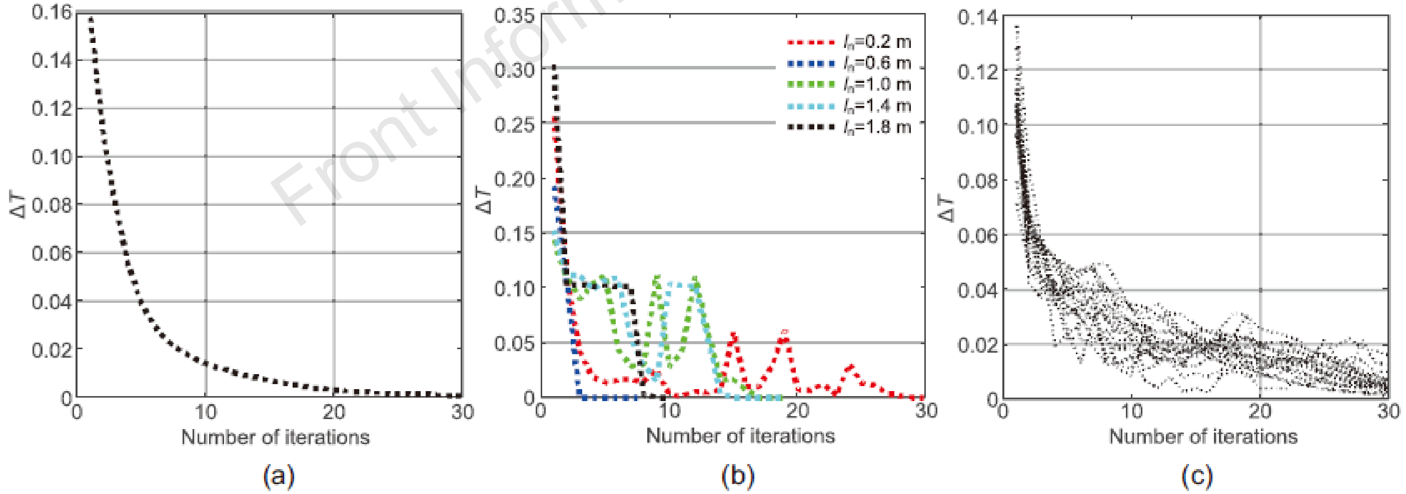

Fig. 7 Convergence results of experiment Gazebo: (a) ICP; (b) NDT; (c) GP registration with different σ_t and l

Major results (convergence, Cont'd)

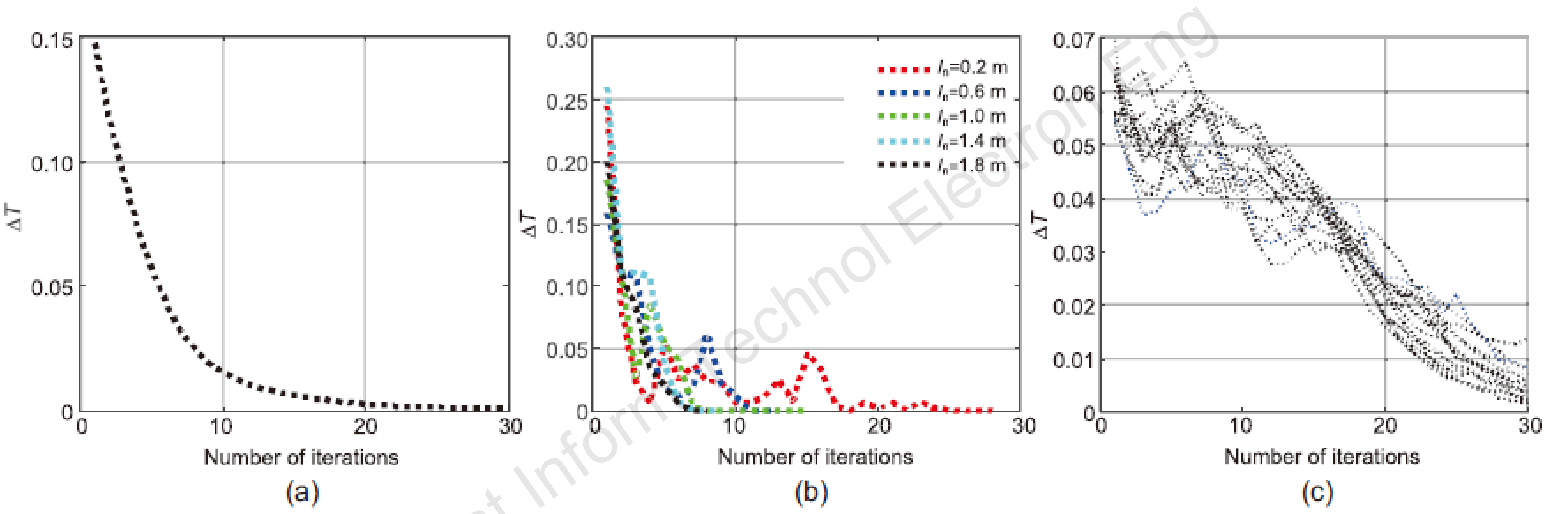

Fig. 8 Convergence results of experiment Wood: (a) ICP; (b) NDT; (c) GP registration with different σ_t and l

Major results (registration)

Table 1 Results of GP registration, normal distribution transform (NDT), and iterative closest point (ICP) in all three experiments, including the rotation error (rad), translation error (m), and runtime (s). The selected parameters of GP registration and NDT are listed as well

Experiment	GP registration	NDT	ICP
Stairs	(h=0.8 m, σ_t=0.04) 0.0006 rad 0.0047 m 23.4 s	(l_n=1.7 m) 0.0032 rad 0.0338 m 230.0 s	0.0110 rad 0.0979 m 22.1 s
Gazebo	(h=0.9 m, σ_t=0.07) 0.0011 rad 0.0106 m 98.3 s	(l_n=1.8 m) 0.0650 rad 0.0253 m 103.9 s	0.0565 rad 0.0566 m 13.3 s
Wood	(h=1.0 m, σ_t=0.04) 0.0239 rad 0.0705 m 163.3 s	(l_n=1.9 m) 0.1049 rad 0.1565 m 226.6 s	0.0984 rad 0.1641 m 23.1 s

Major results (registration, Cont’d)

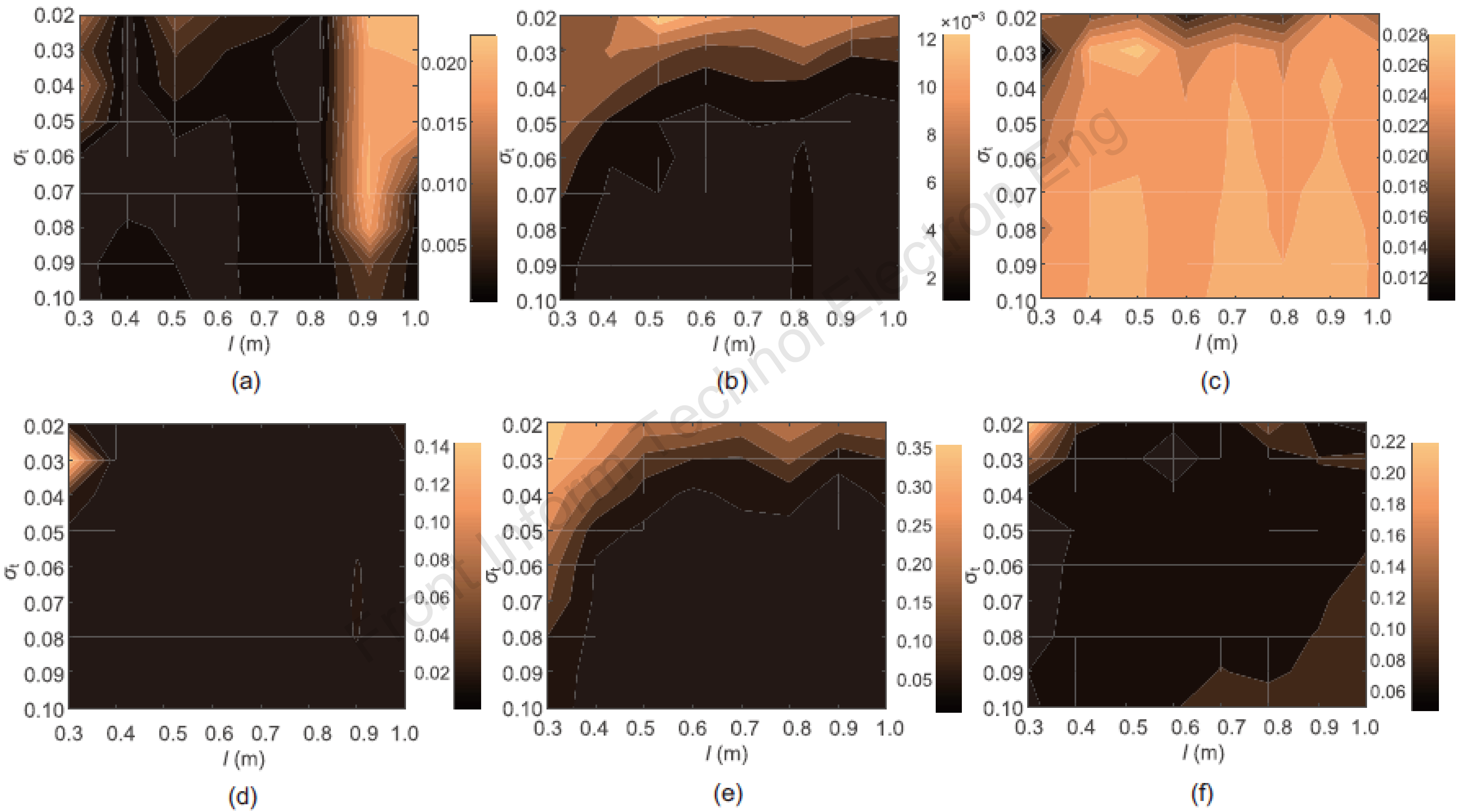

Fig. 9 Contour plots of the rotation errors in experiments Stairs (a), Gazebo (b), and Wood (c) and the translation errors in experiments Stairs (d), Gazebo (e), and Wood (f)

Conclusions

- A new type of map representation has been proposed. The proposed map representation is dense, and its memory consumption is low.

- A new 3D scan-to-map point set registration method has been proposed based on the new type of map representation.

- The robustness and efficiency of the proposed method have been tested and compared against those of two benchmark algorithms on a series of challenging real-world datasets. The experimental results showed that our method exhibits outstanding performance as compared to the other two widely used point set registration methods.