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Evaluation of Digital Map Ability for Vehicle Self-localization

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***Abstract*—Vehicle self-localization based on the matching of Light detection and ranging (LiDAR) scans to the normal distribution (ND) map become more popular in recent years due to the price down and miniaturization of the LiDARs. In such methods, the source of self-localization error can be divided into input scan quality, matching algorithm and map. In this work, we focus on the map, as one of the high potential sources of error. By investigating the erroneous scenarios in the map and comparing their characteristics, we come up with some criteria and requirements for the map to be able to perform self-localization with a needed error. In this work, we propose four factors for quantified evaluation of the map requirements. These factors are feature count factor, layout factor, normal entropy factor, and local similarity factor of the map. We evaluated these four factors in a different part of the map with different scenarios by comparing them with the self-localization error. Experimental results show that the local similarity factor with 0.59 of correlation with the maximum error has the highest contribution to the localization error. For normal entropy factor, feature count factor, layout factor, correlations are 0.42, 0.36, and 0.34 respectively. By applying these four factors, maximum localization error can be modeled with RMSE and R-squared (R^2) of 0.44 and 0.598 respectively. Result of this study can be applied to the dynamic determination of the abstraction ratio of the map and sensor fusion as well.**

I. Introduction

Accurate and robust self-localization is an essential task for autonomous vehicles (AVs). On the other hand, high precision self-localization solution when combined with a prebuilt map can simplify the difficult concept of perception and scene-understanding into a less complicated positioning problem.

In recent years, use of LiDAR for self-localization become more popular due to its price drop and miniaturization. LiDAR-based localization can be divided into two main categories. Map-based and without a map which is also known as SLAM. Since SLAM methods still suffer from error, map-based methods gained more attention in most of the AV platforms. In a map-based method, a raw point cloud of the environment is collected offline using high-end mobile mapping systems (MMSs) [1]. Then, according to the map format, such as point cloud (PCL) map, occupancy map, Normal Distribution (ND) map, vector map, feature map, planar surface map, etc., the map is generated from raw point cloud data. Later in the self-localization phase the scan acquired from LiDAR mounted on the vehicle is matched to the map using one of the point cloud matching algorithm such as variants of iterative closest point (ICP) [2]–[4], normal distribution transform (NDT) [5]–[7] and etc.

In order to achieve accurate localization within the map, in addition to the efficiency of the matching algorithm [8], input scan quality, and other dynamic phenomena, map quality should satisfy some requirements. In another word, the map should meet some specific criteria. Some of these criteria highly related to the environment. For example, in the city environment, there are more structured artifacts than rural places or crop fields. Thus the features for the map-matching can be found easier, and as a result, the localization becomes more accurate [9], [10]. Tunnels, urban canyons, and highways can be assumed as another example. In these scenarios, features needed for longitudinal positioning are not enough, thus the localization error in the moving direction increases. Some other criteria are related to the quality of representation of the environment by the map. Quality of representation highly related to the format and abstraction ratio (resolution) of the map. Quality of representation of the environment in each of the map formats is different. For example in occupancy map [11], space are subdivided into the voxels and environment is represented by occupied cells. In this format, details of the points inside each cell are ignored. On the other hand, in the ND map [6], inside the cells are represented by a Gaussian distribution. In latter format, the map represents the environment with more details. Quality of representation of the environment can be explained in term of the information content of the map. If a map format excludes some details of the map, that means it reduces the amount of information in the map, and as a result, self-localization accuracy degrades.

Besides the map format, resolution or abstraction ratio can lead to information loss as well. If the map resolution is low, it means the abstraction ratio is high, then more details of the map are discarded, and more information is lost. This information loss is different from place to place. In some places of the map, the environment does not have many details. Thus, more abstraction does not lead to more information loss. On the other hand, in some other places of the map, number or arrangement of the features are good enough that the map can be more abstracted and yet preserve the localization accuracy.

To evaluate the map ability for self-localization for each position on the map, aforementioned criteria should be investigated. In this work, we focus on the ND map format which is the map format for the normal distribution transform (NDT) matching. To quantify these criteria for ND map, four map factors are proposed. These factors are feature count factor, normal entropy factor, layout factor, and local similarity factor. Experimental results in Shinjuku, Tokyo, show that these factors highly related to the self-localization error within the map. By applying the principal component

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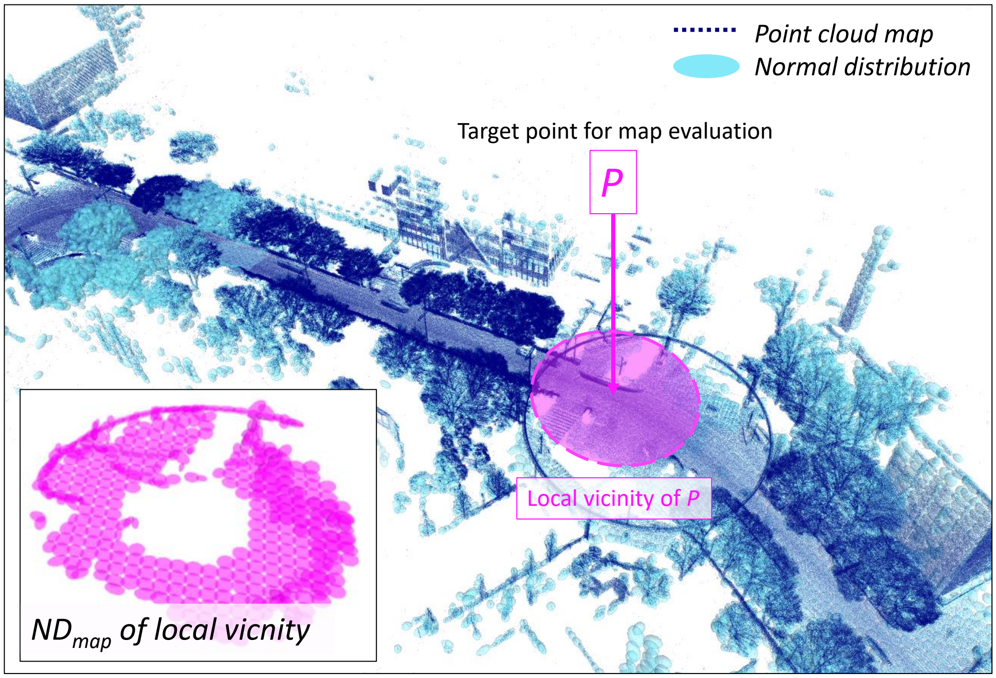

Fig. 1. For each position on the map, features in the range of 25m is extracted (puple features). This region is called local vicinity.

regression (PCR) to these map factors error can be modeled. In this work, only ND map format is investigated. However, the general idea can be applied to other map formats as well. The result of this study can be applied to the dynamic determination of the abstraction ratio of the map and sensor fusion as well.

The rest of this paper is organized as follows. Section II introduces related works. Section III describes the proposed factors, and section IV evaluates these factors and contribution of each factor to the localization error by applying the experiments. Finally, section V concludes this paper.

II. Related Works

Evaluation of the map ability for localization can be considered as a detection of misaligned scan to the map. The misaligned scan can be detected with the measures used for alignment. For example, if the registration method is ICP [3], root mean square (RMS) distance of the scan and map can be assumed as a measure to detect the misalignment. In RMS-based misaligned detection, smaller RMS shows better matching quality. On the other hand, if alignment algorithm is based on NDT [5], [7], NDT score and Hessian can be used as a measure to detect the misaligned scans. In this measures, better alignment shows higher NDT score and smaller eigenvalues in NDT Hessian. However, in these methods, measures used for alignment is directly used for misalignment detection which is not reasonable. Therefore, C. Dylan et al. combined aforementioned measures such as mean square error, NDT score, NDT Hessian, with a mean square error of odometry-transformed and NDT-transformed poses to achieve new measure [12]. In [13], consistency between the normals of the scans is used as a measure. In [10], A. Hakan et al. considered these measures as a point cloud classifier to make a binary classification of the aligned and misaligned scan pairs. In [10], authors used aforementioned measures as well as plane extraction classifier and surface interpolation measure classifier [14] to make a more strong binary classifier.

However, in order to apply aforementioned measures for the map evaluation, in addition to the map, corresponding scans of the LiDAR should be available. One of the examples is [9], in which N. Akai et al. in order to predict the localization error in different place of the map, a vehicle once traverses full paths, and error model is calculated empirically. Later in the localization phase, experimentally determined uncertainty (error model) is used for the position rectification. One of the drawbacks of this method is that it needs a high amount of field experiments. Contrary to this method, in our proposed method, localization error can be modeled from the map without a field test. However, error model in [9] consider the input scan quality such as density of the scan as well, while in this work, input scan quality is inferred from map factors and for sure former can model more precisely.

In [15], O. Vysotska et al. used the building information from the open street map (OSM) as background knowledge to predict the erroneous part of the paths to improve the graph-based SLAM. However, OSM does not contain detailed shape of the building or irregularity in the building walls which highly affect the map matching results. S. Thompson et al. use the auto-correlation measure to detect the effectiveness of the 3D polygon map for localization.

III. Definition of the Factors

In this section, proposed factors are defined. Factors are calculated based on the features (NDs) in the local vicinity of the sample point. In this work, the range of local vicinity is 25 m. ND map of local vicinity is shown in Fig. 1.

A. Feature count factor of the map

The first factor is feature count. For map matching techniques the map should contain features so that the input

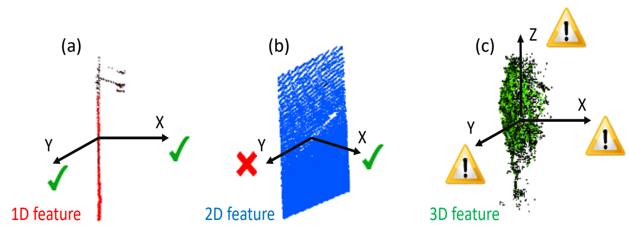

Fig. 2. Definition of 1D, 2D and 3D uncertain features. 1D uncertain features can perform the positioning for 2 dimensions. 2D uncertain features can localize in 1 dimension and 3D uncertain features has high uncertainty so its contribution to finial stage of optimization is very low.

scan can be matched with those features. The type of features is different in each of the map format and matching methods. For example, in the point cloud map, the features are points, in the ND map the features are NDs and in the case of vector map and planar surface map the features are vectors and planar surfaces respectively. For better self-localization, plenty yet high-quality features are required. Generally, the quality and number of extracted features are related to the environment.

In addition to the number of features, in NDT, the shape of NDs in the map might contain important information as well. As the normal distribution lead the input scan to its optimum position, the contribution of each ND to the optimization is related to the shape of NDs. If the shape is more like a sphere, it means that the ND is more uncertain and the portion of the contribution is less. In other words, it cannot help the alignment of the input scan to its proper position. In this work, these features are called 3D uncertain features (3D-ND) (Fig. 2(c)). Having 3D-ND increase the uncertainty of the whole map, however, having of them is better than having no features. The other group of features is 2D-ND. This type of features are plane-like features and can lead the input in one dimension. It can lead the scan to the direction parallel to its normal. In Fig. 2(b) it can only correct the position of the wall in the X direction. In other words, the uncertainty of 2D-ND features is high in 2 dimensions. Thus it can be used to align

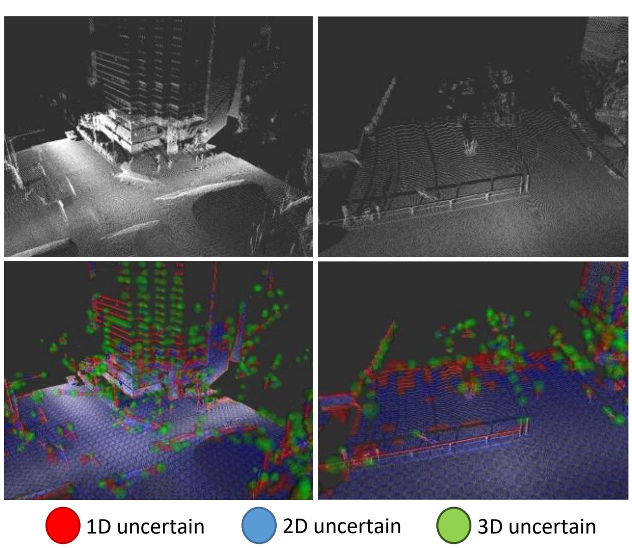

Fig. 3. 1D, 2D and 3D uncertain features. The red features are 1D uncertain, the blue features are 2D uncerain, and the green features are 3D uncertain. As the point density of some part of the building is not high, these part forms 1D or 3D features instead of 2D features. And finally the vegetation and scattered objects form 3D-ND (green features).

the scan in only one dimension. These features (2D-NDs) are more useful in the matching and thus in the localization comparing to 3D-NDs. The other group of features is 1D-ND. This type of features has the uncertainty only in one dimension. In other words, it has a certain value in 2 dimensions and can lead the input scan in 2 dimensions to register on the map. 1D-ND features are shown in Fig. 2 (a). As shown in the figure, this type of feature can lead the input scan in X and Y dimension. It cannot fit the position of input scan in the Z dimension. 1D-ND is more useful than both 2D-ND and 3D-ND. Usually, vegetation and trees and especially scattered objects make 3D-ND features. Building walls can make 2D-ND features and poles and edges make 1D-ND features. In Fig. 3, 1D, 2D and 3D ND are shown with different colors. In Fig. 3, ground forms a very clean 2D-ND (blue features). Also, some part of the building walls forms the 2D-ND. Pole-like features form the 1D-ND features (red features) in this figure.

For ND map, the number of NDs is the feature count. For the quality of the features, dimension uncertainty is calculated for all features (NDs). The dimension of uncertainty for each feature is calculated inspired by [16] as follows:

First, for each normal distribution, Eigenvalues are calculated. Consider that the Eigenvalues are λ_1, λ_2, and λ_3. From Eigen values the standard deviations are calculated as follows:

$$\forall i \in [1,3] \qquad \sigma_i = \sqrt{\lambda_i} \tag{1}$$

Where i is the index of Eigenvalues. Using standard deviation, three behavior for each features are defined as follows:

$$a_{1D} = \frac{\sigma_1 - \sigma_2}{\sigma_1}, a_{2D} = \frac{\sigma_2 - \sigma_3}{\sigma_1}, a_{3D} = \frac{\sigma_3}{\sigma_1}, \tag{2}$$

Where a_{nD} is the n dimension uncertainty behavior of the feature. If $a_{1D} \gg a_{2D}, a_{3D}$, it means that the feature is a 1D uncertain feature (pole-like feature) and If $a_{2D} \gg a_{1D}, a_{3D}$, it means that the feature is a 2D uncertain feature (wall-like feature). Instead of directly use a feature count as a factor, the ratio of each factor over the total feature count are calculated as follows:

$$mD\ count\ ratio = \frac{total\ number\ of\ mD\ features}{total\ number\ of\ features} \tag{3}$$

Where m is the dimension which can be 1, 2, and 3. This factor is called feature count ratio.

B. Layout factor of the map

In some part of the map, there might be plenty of feature count factor, but these features are all placed in one corner of the map. This situation is shown in Fig. 4(a). This uneven distribution of the map features can cause the localization error. The concept of distribution of the features comes from GPS-based localization. In the GPS-based localization, if satellites are not distributed evenly, in another word, satellites lean in one region, then the position will be erroneous. This is because each of the pseudo-ranges calculated from each satellite has an error by itself. If all satellites are lean in one small region, then they cannot compensate each of the pseudo range error, and this input error highly appears in the output.

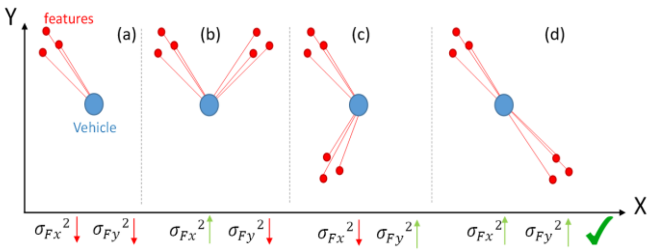

Fig. 4. Feature layout and the layout factor. blue circle in the center is the vehicle position and small red circles show the features of the map which is captured by laser scanner (ND map) If the features are distributed evenly then the layout factor is high.

The ratio that how much the input data affect the output location result is formulated by Geometrical Dilution of Precision (GDOP) in GPS [17]. We inspired from GDOP and defined a map factor called feature DOP (FDOP). FDOP formulates the layout factor of the map.

Assume the vehicle position is GPS receiver position and satellites are the features. Thus, the position of the vehicle is $P = (x, y, z)$ and the position of the feature i is $F_i = (x_i, y_i, z_i)$ and the distance from the feature i to the vehicle is R_i. Matrix A is obtained as follows:

$$A = \begin{bmatrix} \frac{(x_1-x)}{r_1} & \frac{(y_1-y)}{r_1} & \frac{(z_1-z)}{r_1} \\ \frac{(x_2-x)}{r_2} & \frac{(y_2-y)}{r_2} & \frac{(z_2-z)}{r_2} \\ \vdots & \vdots & \vdots \\ \frac{(x_m-x)}{r_m} & \frac{(y_m-y)}{r_m} & \frac{(z_m-z)}{r_m} \end{bmatrix}, \tag{4}$$

From multiplication of A and its transpose,

$$Q = A^T A = \begin{bmatrix} \tilde{\sigma}_x{}^2 & \tilde{\sigma}_{xy} & \tilde{\sigma}_{xz} \\ \tilde{\sigma}_{xy} & \tilde{\sigma}_y{}^2 & \tilde{\sigma}_{yz} \\ \tilde{\sigma}_{xz} & \tilde{\sigma}_{yz} & \tilde{\sigma}_z{}^2 \end{bmatrix}, \tag{5}$$

Q is obtained which is the covariance matrix of the position of the features related to the vehicle. Finally, FDOP is calculated as follow:

$$FDOP = 1/\sqrt{\tilde{\sigma}_x{}^2 + \tilde{\sigma}_y{}^2 + \tilde{\sigma}_z{}^2}, \tag{6}$$

Fig. 4 shows the relation between the layout of the features and FDOP components. As Fig. 4(a) shows, features are lean to one corner and layout are weak in both X and Y. So the FDOP is high and might cause localization error. In Fig. 4(b), the X layout is acceptable, but the Y layout is not acceptable. Thus, the localization accuracy might be good only in the x-direction. Finally, in Fig. 4(d), both X layout and Y layout are excellent. Thus the FDOP value is low, and as a result, accurate self-localization can be obtained. The FDOP factor of the map is highly related to the environment and resolution does not affect it.

C. *Normal entropy factor of the map*

In some part of the map, we might have the situation such as tunnels, urban canyons, and highways in which the features for longitudinal positioning are very few. These situations are shown in Fig. 5. In these situations, the longitudinal positioning is erroneous. In Fig. 6(A, B), the vehicle cannot observe any feature for longitudinal positioning. However, in position C, a vehicle observe lateral wall which can be used for longitudinal positioning. In both A and B scenarios, the previously defined factors, the feature count factor, and layout factor are good enough. In the case of feature count, we have plenty of the features which surround the vehicle. In the case of layout factor, as the features surround the vehicle evenly, FDOP is small as well. Therefore by evaluating these two factors, a shortcoming of the map cannot be detected. Thus, we need a new factor which is called normal entropy factor.

Fig. 5. Different situation that show the localization in longitudinal has error.

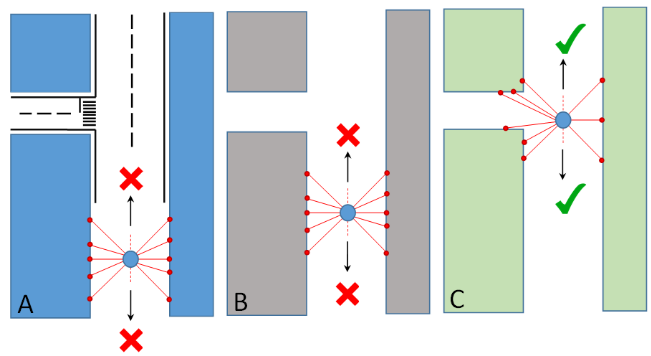

Fig. 6. Scenario in which localization has longitudinal error. In A and B no lateral walls are obrevable thus the longitudinal position cannot be obtainbed. In C vehicle can observe the lateral walls thus it can perform longitudinal positioning as well.

To calculate normal entropy factor, first the normal of each ND is obtained from its covariance matrix. Vector corresponds to the smallest Eigenvalue is normal. For each of the normal, Azimuth and altitude angle are calculated. The calculated azimuth and altitude are binned into a histogram with 8×8 bins. Then the entropy of this histogram is calculated. Suppose that $P(\theta, \varphi)$ is the probability that the azimuth and altitude angle are θ, φ respectively. The entropy for this probability distribution function is calculated as follows:

$$H_N(\theta, \varphi) = \sum_{i=1}^{b} \sum_{j=1}^{b} -p(\theta_i, \varphi_j)\log(p(\theta_i, \varphi_j)), \tag{7}$$

Where b is the number of angle bins which is 8. If $H_N(\theta, \varphi)$ is high, the distribution of normals are more even and, this means that the features are facing to a different directions. Small $H_N(\theta, \varphi)$ means most of the normal are facing to the same direction and this make the positioning difficult. Normal entropy factor can be affected by the environment and grid resolution.

D. *Local Similarity factor of the map*

Some position in the map might have similar features that cause the self-positioning difficult. Fig. 7 shows this scenario.

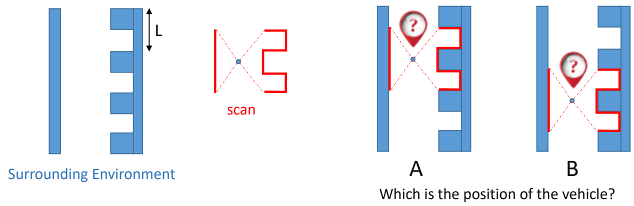

Fig. 7. Similarity in the map cause the positioning uncertainty. Longitudinal position cannot be obtained.

The blue shapes are the buildings which surround the vehicle. The red lines are LiDAR observation. By referring to the input scan and map, the position of the vehicle can both A and B. In the scenario shown in Fig. 7, again all three factors above cannot detect the shortcoming of the map. Therefore, a new factor is defined which is called local similarity factor of the map. Local similarity or similarity is a well-known term in image processing [18] and point cloud processing[19]. For point cloud processing, the local similarity is used for point cloud matching, denoising, and compression. In [19] Kanji used the similarity metrics to detect the change, i.e., the anomaly of local maps built by a mobile robot at multiple different times. The local similarity of the map is an unwanted phenomenon in map-matching. In order to quantify the local similarity factor, score entropy is defined and formulated.

For a specific position on the map, one circular region of points are extracted as shown in Fig. 1. This point set is assumed as input and target at the same time. Assume the input point set is A and the target point set is $(A = B)$. ND map from B is generated $(N_{B,})$. The input is iteratively moved over the target with transformation vector $T = (x, y, z, yaw, pitch, roll)$ and likelihood distribution is calculated using the same formulation in NDT registration [20]. Likelihood distribution can be shown as:

$$L = \sum_{x=-2.0}^{2.0} \sum_{y=-2.0}^{2.0} L(x, y) \tag{8}$$

$$L(x, y) = \text{Score}\ (\text{A}, N_{B,}\ \text{T}(\text{x}, \text{y}, 0,0,0,0)) \tag{9}$$

Where A is input point set, $N_{B,}$ is ND map from the point set B and T is the transformation vector in which only x and y changes.

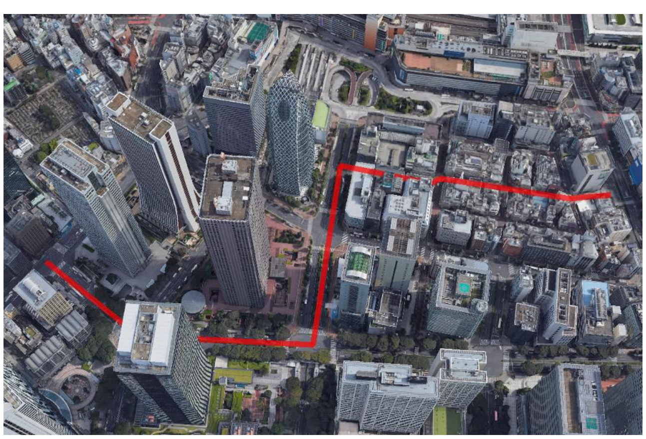

Fig. 8. The experimental area around Shinjuku, a dense urban area in Tokyo, Japan.

Fig. 9. Our experimental vehicle. Front Velodyne VLP-16 is used for mapping and it is tilted to scan the environment densly (pitvh -80°). Top VLP-16 used for localization.

At the center point $L(0,0)$ the likelihood value is maximum. If this region of the map has high local similarity, score in different places has maximum and thus the likelihood distribution L has more peaks. If this region of the map has low local similarity, L has less peaks. To detect the characteristics of distribution L, L is assumed as a probability distribution function and entropy over L is calculated. The entropy result is called score entropy. If the map has local similarity, then as it has more peaks, the peak of curve become more flat, thus the score entropy become lower. Map with high local similarity is more likely to cause an error. Therefore score entropy has an inverse relation with localization error. Score entropy is highly related to the environment and resolution of the map.

IV. FACTOR EVALUATION

To evaluate the contribution of each factor in the map matching-based localization error, an experiment was conducted in Shinjuku, a dense urban area of central Tokyo, Japan (Fig. 8). Streets around Shinjuku is surrounded by skyscrapers, tall buildings, narrow streets, and trees. For the map generation, we equipped our vehicle with two VLP-16 laser scanners which one of them was mounted horizontally (Fig. 9(B)) to maximize the sensor range for SLAM and the other one was configured to point down (pitch -75°) to densely scan the details of building surface for the mapping (Fig. 9(A)). To avoid the scan distortion due to the motion of the vehicle, the vehicle's velocity was below 2 m/s while the frequency of the laser scanner was set to 20 Hz which limits the distortion in each scan to less than 10 cm. The final map was generated using the tilted Velodyne only. Fig. 10 shows a part of the generated map. Then, an ND map with a large grid size (4.0m grid) was generated from the point cloud map to estimate the factors and error of the map matching-based localization.

In the next step, the vehicle is traversed through the path once again, but this time for localization. The data collected form VLP-16 which was mounted horizontally was used to match with 4.0m ND map and perform localization. Sample points for the map evaluation are selected along the trajectory with 1.0m intervals. For each sample point, localization error and map factors are calculated. In order to calculate the localization error for each sample point, map matching was performed $11 \times 11 = 121$ times for different initial positions

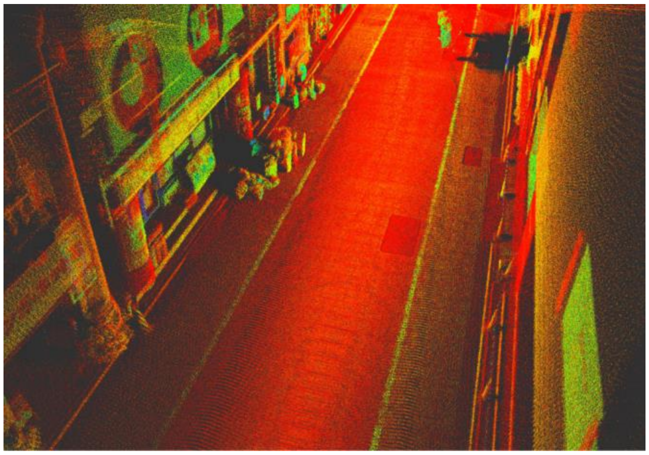

Fig. 10. A part of the map used for evaluation and self-localization. As the point cloud map is made from VLP-16 which is tilted, the density of the data is high.

(within 2.0 meters to four sides with an interval of 0.4m), and the mean and maximum error was calculated. In the error calculation, the map matching using 1.0m-ND map was considered as the ground-truth. For the same sample points, map factors are calculated as well. Map factors are calculated only based on the ND map in the local vicinity of sample point and input scan is not considered.

The correlations between the map factors and the localization error are shown in TABLE I. The red cells have a higher positive correlation, and the green cells have a higher negative correlation, and the yellow cells indicate a low correlation. One of the signs that a map factors and the localization error have a cause and effect relation is that a high correlation should be found between them. Among the map factors, the local similarity factor (score entropy) has the highest correlation with the maximum localization error (-0.592). The lower similarity entropy indicates a higher local similarity in the map which makes the map matching more difficult. It means that, if the similarity entropy is decreased, probably the maximum localization error will be increased. After the similarity entropy, the normal entropy, D3_ratio, and FDOP are the most correlated factors to the maximum localization error with the correlations of -0.426, -0.36, and 0.344 respectively. Since the correlation between the similarity entropy and other factors are relatively low, it can be considered as a key factor for predicting the maximum localization error. The low correlation between the normal

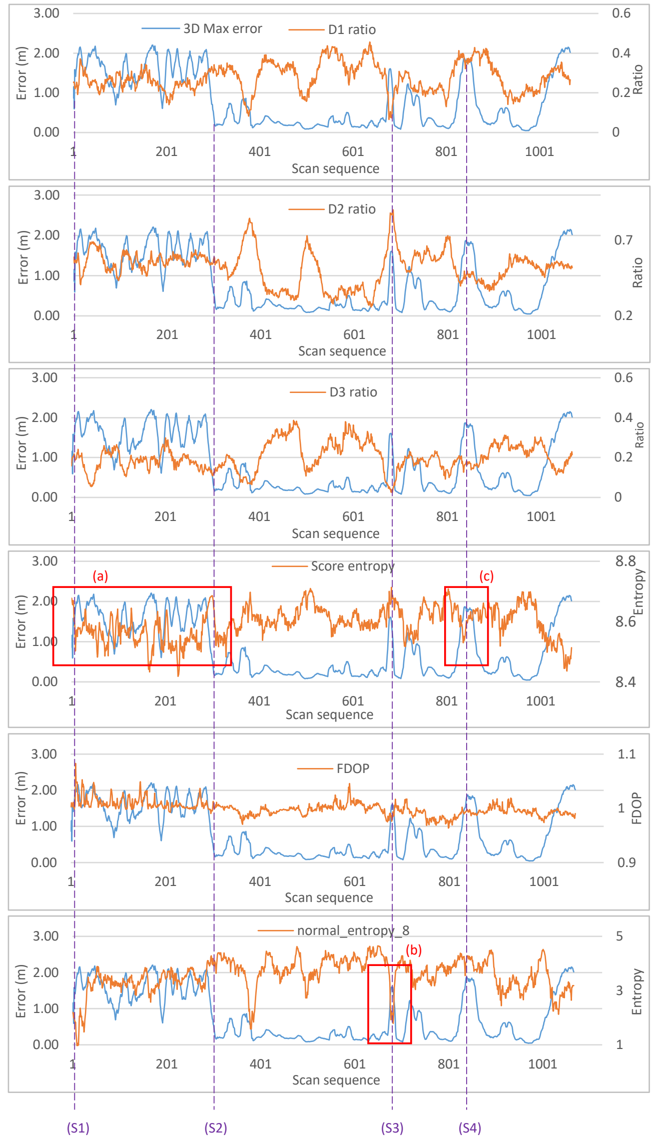

Fig. 11. Comparison of different factors with 3D maximum error. For each figure, blue graph is 3D maximum error and orange graph is values of factors. Normal entropy factor is calculated for 8×8 bins.

entropy and similarity entropy shows that they can reveal the different source of the maximum error. On the other hand, as the correlation between the D3_ratio and D2_ratio is very high

TABLE I. CORRELATION OF EACCH FACTORS WITH EACH OTHER AND WITH MAX AND MEAN ERRORS.

	Map Evaluation Factors						**Error**	
	Score entropy	**D1_ratio**	**D2_ratio**	**D3_ratio**	**FDOP**	**Normal entropy**	**Mean 3D Error**	**Max 3D Error**
Score entropy	1.00	-0.13	0.08	0.00	-0.29	0.14	-0.38	-0.59
D1 _ratio	-0.13	1.00	-0.82	0.31	0.18	0.47	-0.17	-0.11
D2_ratio	0.08	-0.82	1.00	-0.80	-0.19	-0.50	0.19	0.29
D3_ratio	0.00	0.31	-0.80	1.00	0.12	0.33	-0.14	-0.36
FDOP	-0.29	0.18	-0.19	0.12	1.00	-0.14	0.13	0.34
Normal entropy	0.14	0.47	-0.50	0.33	-0.14	1.00	-0.39	-0.43
Mean 3DErr	-0.38	-0.17	0.19	-0.14	0.13	-0.39	1.00	0.59
Max 3DErr	-0.59	-0.11	0.29	-0.36	0.34	-0.43	0.59	1.00

1.0

-1.0

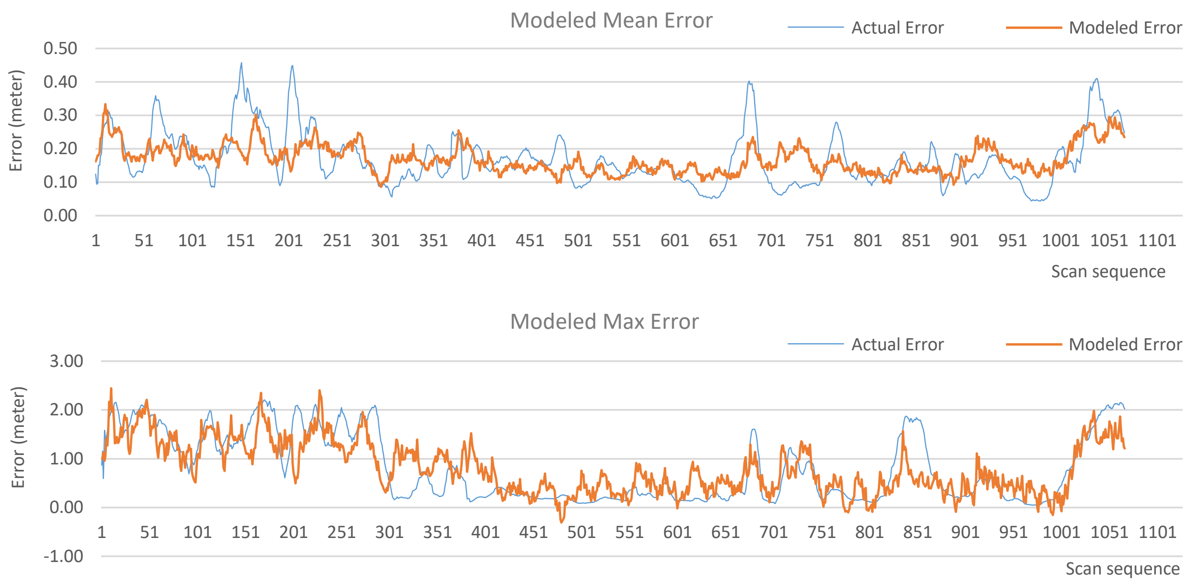

Fig. 12. Comparison of the actual 3D error and the modeled error using factors. Top graph shows the mean error and botm graph shows max error.

(-0.798), the D2_ratio does not provide considerable additional information for the maximum error prediction.

Fig. 11 shows the value of each factor comparing to the maximum localization error for the experimental route. In region (a) and (c) where the similarity entropy is lower compared to the other parts, the localization error is higher. The same phenomenon happens for most of the peaks of the maximum error. However, in region (b) the similarity entropy stayed high while the localization error was increased. While the similarity entropy failed to describe the maximum localization error in region (b), the normal entropy factor clearly describes the error source.

As can be seen in *TABLE I*, the correlation between the factors and mean error is lower compared to their correlation with the maximum error. The similarity entropy and normal entropy, however, still have a considerable correlation with the mean error with the value of -0.39 and -0.379 respectively.

Finally, we modeled both the mean and maximum localization error using Principal Component Regression (PCR). Fig. 12 shows the result of PCR. As could be expected from the correlation table, we could model the maximum error much better than the mean error. The RMSE of the predictions were 0.44 and 0.068 for the maximum and mean error respectively. Moreover, the R-squared (R^2) for the maximum error was 0.598. It worth to mention that in this research the effects of the factors on the yaw error are not evaluated.

V. Conclusion

In this work, we have focused on the map, as one of the high potential sources of error in the map-matching based self-localization. By investigating the erroneous scenarios in the map and comparing their characteristics, we have introduced some criteria and requirements for the map to be able to perform self-localization with a needed error. In this work, we have proposed four factors for quantified evaluation of the map requirements. These factors are feature count factor, layout factor, normal entropy factor, and local similarity factor of the map. By applying the experiments in Shinjuku, Japan, we have evaluated these four factors in a different part of the map with different scenarios by comparing them with the self-localization error. Experimental results have shown that the local similarity factor with 0.59 of correlation with the maximum error has the highest contribution to the error. Correlation value of normal entropy factor, feature count factor, layout factor are 0.42, 0.36, and 0.34 respectively. The proposed factors can model the maximum error better than mean error. The result of this study can be applied to the dynamic determination of the abstraction ratio of the ND map and other formats of the map which be a potential future work of this study.

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