Proceedings of the 2009 IEEE
International Conference on Robotics and Biomimetics
December 19 -23, 2009, Guilin, China

Robust Laser Scan Matching in Dynamic Environments

Hee-Young Kim, Sung-On Lee and Bum-Jae You

***Abstract*— this paper presents a robust laser scan matching algorithm in dynamic environments. Scan matching is thought to be an essential function for mapping and localization of mobile robots. Our method is based on the *RANdom Sample and Consensus (RANSAC)* algorithm known for its good robust parameter estimation of the model parameters. Different from the existing scan matching methods for mobile robots, we only use the raw data of laser scanning without odometer information to find the transformation between two given laser data sets. Our method does not require any feature extraction and also need not initial estimation to reach global optimum. We demonstrate the practical usability of the proposed approach through Experiment.**

Index Terms—laser scan matching, range sensor, RANSAC, robot pose estimation, localization, map building

I. INTRODUCTION

AUTONOMOUS mobile robot navigation in an unknown environment is a well-known issue and localization is a key for this works. There exist many approaches for robot navigation and localization [1-5]. One intuitive and essential method is using laser distance scanning to estimate current pose of robot, it called scan matching algorithm [5]. Scan matching is originally made for range image registration in 3D Computer Vision [6-8] [12-15] [20]. However, in Robotics it use for robot pose estimation and correction; if we know previous posture and laser scan data and current laser scan data, we can estimate current posture of robot by scan matching. Scan matching for robot pose estimation method can classify feature-based matching and iterative update approaches especially. Feature-based approaches [9-11] have an advantage that does not need initial parameter estimation of transformation. However, it needs a preprocessing step of feature extraction from scan data. If the data have few prominent features like outdoor navigation environments it has excessively possibility of fail matching them. Another is iteratively-update approaches [8] [9] [16-18]. Iteratively update approaches are good performance in unknown environments even if they need a good initial estimation to prevent the iterative process from being trapped in a local minimum. For good initial estimation method to cover this disadvantage is an iterative matching range point (IMRP) algorithm which combined in iterative dual correspondence algorithm (IDC) [17]. Nevertheless, its computational cost to find corresponding line is expensive and it has not enough matching performance in dynamic environments; a dynamic environment is a mixture of static and moving objects [19]. Several mobile robots work in dynamic environments even indoor robot. Iterative dual correspondence-Sector (IDC-S) is one research to solve this disadvantage of IDC [18].

We suggest laser scan matching method in dynamic environment but not iteratively update scheme named *Corresponding Vector Fitting SAC* (CVFSAC). Our algorithm searches all possible case of matching and select best one of matching rate using given two previous and current laser scan data pair. It does not require any preprocessing for feature extraction and not need to set good initial position.

This paper is organized as follows: Section II introduces overall procedure of our new scan matching method. Section III explains it in detail. Section IV shows post processing to find optimal parameter estimation. In Section V, we suggest some acceleration strategies for fast CVFSAC. Finally we demonstrate some experimental results and conclude our proposal.

II. OVERALL PROCEDURE OF SCAN MATCHING

Fig. 1 shows procedure of suggested algorithm. Let two laser

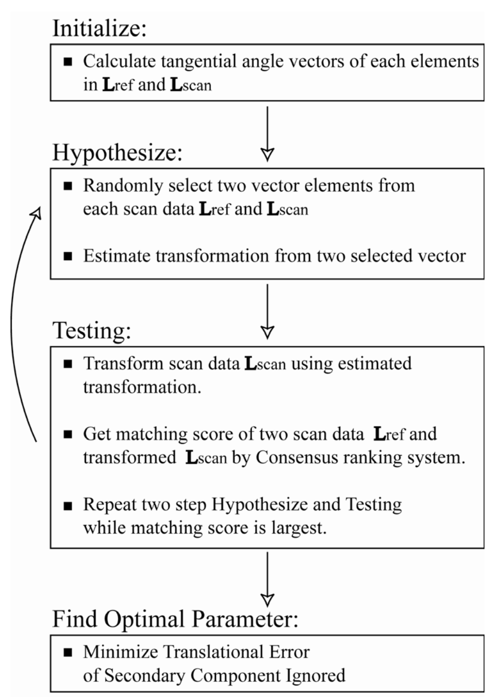


Fig.1. **Procedure of CVFSAC algorithm**

Hee-Young Kim is with University of Science and Technology, Korea and with Center for Cognitive Robotics Research, Korea Institute of Science and Technology, Seoul, Korea.

Sung-On Lee and Bum-Jae You are with Center for Cognitive Robotics Research, Korea Institute of Science and Technology, Seoul, Korea., Address: Cheong Ryang. P.O. Box 131, Seoul, South Korea.

(e-mail: {heeykim, solee, ybj}@kist.re.kr)

978-1-4244-4775-6/09/$25.00 © 2009 IEEE.

scan data, reference model data L_{ref} and scan data L_{scan}, be given. It find best configuration by two steps: *Hypothesize and Testing*. This main concept is originated in *RANdom Sample and Consensus algorithm (RANSAC)* [6] [20]. Ransac algorithm is robust parameter estimation method for model-based estimation using data contaminated by outliers [6].

III. CORRESPONDING VECTOR FITTING SAC

Now we illustrate a laser range scan data model then explain how to find next posture of robot using this model.

A. Laser Range Scan Data Model

Let assume a laser distance measurement scanner generates distance data array from 0° to 180° ranges with 0.5° angular resolution and $\pm 15mm$ measurement error. The laser range scan data array model L is:

$$L = \{ d_i \mid i = 0, \cdots, n \quad d_i \in \mathbb{C} \} \tag{1}$$

And each measured elements represent:

$$d_i = |a_i| e^{j\theta_i} + \varepsilon \tag{2}$$

Where:

$|a_i|$: Measured distance at range angle θ_i

θ_i: $\{\textit{Angluar Resolution Unit}\} \times i$

ε: Measurement error

If this data is measured at posture $P(x, y, \theta)$ in global coordinate in Cartesian, real position of measured is on:

$$d_i = |a_i| \{ (\cos(\theta_i + \theta) + x) + j(\sin(\theta_i + \theta) + y \} + \varepsilon \tag{3}$$

Let two scan data sets, the reference data L_{ref} at initial posture $I(0,0,0^\circ)$ and the scan data L_{scan} at unknown posture $U(t_x, t_y, \theta_r)$, be given:

$$\begin{aligned} d_{ref} &= |a| \{ \cos(\theta_a) + j\sin(\theta_a) \} + \varepsilon \\ d_{scan} &= |b| \{ (\cos(\theta_b + \theta_r) + t_x) + j(\sin(\theta_b + \theta_r) + t_y) \} + \varepsilon \end{aligned} \tag{4}$$

Where:

$d_{ref} : d_{ref} \in L_{ref}$

$d_{scan} : d_{scan} \in L_{scan}$

Now scan matching problem is finding unknown parameter $U(t_x, t_y, \theta_r)$ when two scanned curves are well overlapped. it seems like to find 2D linear transformation parameters and free 3 degree-of-freedom (DOF) system. Now, let call unknown parameter $U(t_x, t_y, \theta_r)$ as scan matching parameter.

B. Corresponding Vector

To solve this 3 DOF equation simply we need to find two corresponding position pairs. Badly Laser scan data is not easy to find exactly same two measured position pairs (Fig. 2) Accordingly we find only one measured position pair since it is easy than find two pairs relatively. One measured position pair can constrain 2 free parameters. To force one left free parameter, we calculate tangential angle vector between found measured position pair and each followed measured position

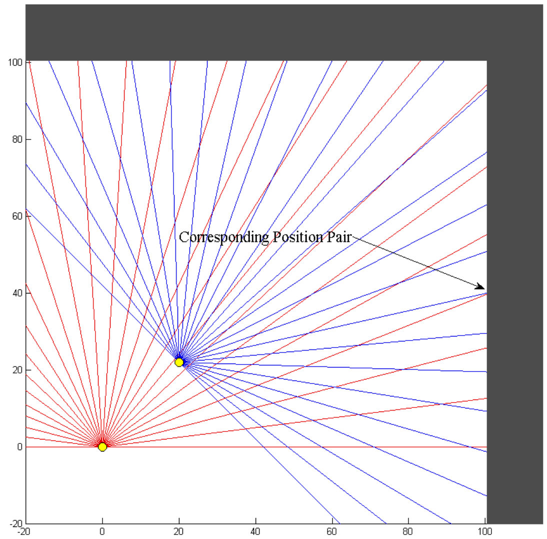


Fig.2. **Laser-range scanner measured same object but in different posture in MATLAB** [Red at $(0,0,0^\circ)$; Blue at $(20,22,-45^\circ)$], but it is hard to find same corresponding position pairs.

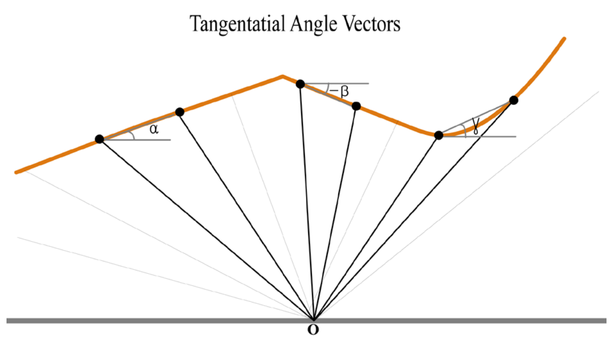


Fig.3. **Tangential Angle Vectors:** tangential angle vector can find one position and next measured laser distance position. α is positive sign tangent angle. β is negative sign tangent angle. γ shows tangential angle in conic. Tangent vector sign signal is important to find scan matching parameter.

(Fig. 3).

Let one reference position element d_{ref} have a tangential angle vector α from its next adjacent one d_{ref+1}, and one new scanned position d_{scan} have a vector β from following one d_{scan+1}. This two elements (d_{ref}, α) and (d_{scan}, β) call a corresponding vector pair. We can estimate scan matching parameters from equation (3) and this corresponding vector pair candidate:

$$\begin{aligned} \theta_r &= \beta - \alpha \\ t_x &= |a|\cos\theta_a - |b|\cos(\theta_b + \theta_r) \\ t_y &= |a|\sin\theta_a - |b|\sin(\theta_b + \theta_r) \end{aligned} \tag{5}$$

Fig. 4 illustrates how to find it in geometrically.

C. Consensus Ranking System

Section 2.B shows how to estimate scan matching parameter if we got a corresponding vector pair candidate; one

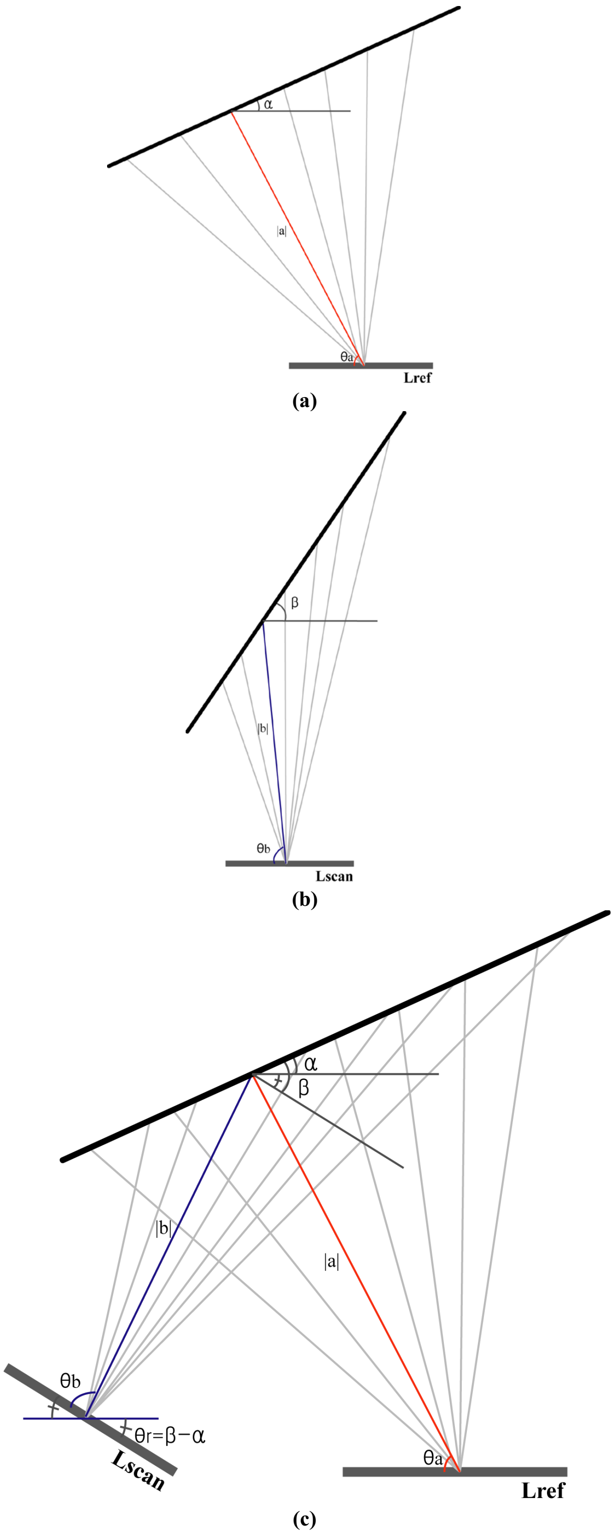


Fig.4. **Match two laser-range data using a corresponding vector pair.** (a) and (b) show laser scan data L_{ref} and L_{scan} with their corresponding vectors(color line). (c) It can match and find unknown scan matching parameters.

corresponding position and their tangential angle vector. In the laser scan data, it is difficult to find corresponding vector directly. Accordingly, we use RANSAC technique to find a corresponding vector pair which best overlapping two curves.

Hypothesis Step: Select randomly two vectors from each laser-range scan data L_{ref} and L_{scan}. Assume that a corresponding vector pair and calculate scan matching parameter candidate $\widehat{U}(t_x, t_y, \theta_r)$. Transform L_{scan} to $\hat{L}_{scan}$ using this estimated scan matching parameter.

Testing Step: Rank according to how many two laser scan points of each candidate matched and terminate when the largest rank scored pair and parameter found. To do like that we need a consensus ranking system for laser scan matching how many two laser scan curve L_{ref} and $\hat{L}_{scan}$ match. The consensus ranking system R make a corresponding vector pair candidate scores using below criteria:

$$R(L_{ref};\hat{L}_{scan}) = \sum_{i=0}^{N} \rho(b_i, a_C)$$
$$\rho(b_i, a_C) = \begin{cases} 1 & \|b_i, a_C\|_E \le \delta \\ 0 & othrewise \end{cases} \tag{6}$$

Where:

L_{ref} : Reference laser-range data

$\hat{L}_{scan}$: Transformed scan laser-range data

R : Consensus Ranking System

b_i : An element of L_{scan}

a_C : Closest point in L_{ref} with b_i

δ : Matching criteria

For the matching criteria, we use L-2 Norm of each measured position and next measured position:

$$\bar{d} = \frac{1}{N-1}\sum_{i=1}^{N-1}\|d_i, d_{i+1}\|_E$$
$$\delta = \{\text{Criteria Ratio}\} \times \bar{d} \tag{7}$$

If Criteria Ratio set too high, the rank system gives a poor rank score affected by outlier even though we have been chosen a best corresponding vector pair. On the contrary, if we set it too low the system gives a poor rank score as the same reason of Fig. 2. We found 0.2 Criteria Ratio is good performance by our experiments.

IV. Find Optimal Parameter

CVFSAC find reliable scan matching parameter by above procedures. However, our method sometimes fails to find optimal parameter directly. Because of consensus ranking system ignores secondary component of data if primary component data is too large than secondary one. A laser scan data can be separated two component; primary and secondary. The primary component is an axis which has a large portion of laser-range data and the secondary component is another axis which of remained. Fig 5 explains this primary and secondary component.

Consequently we use iterative closed point (ICP) [13] algorithm to reduce this error and to get optimal matching parameters.

1) Eliminate primary component data of reference and transformed data.
2) Find closet point pair from each laser-range data.

3) Select same distance of closet point pair to remove outlier: use 2.5σ of distance set [13].

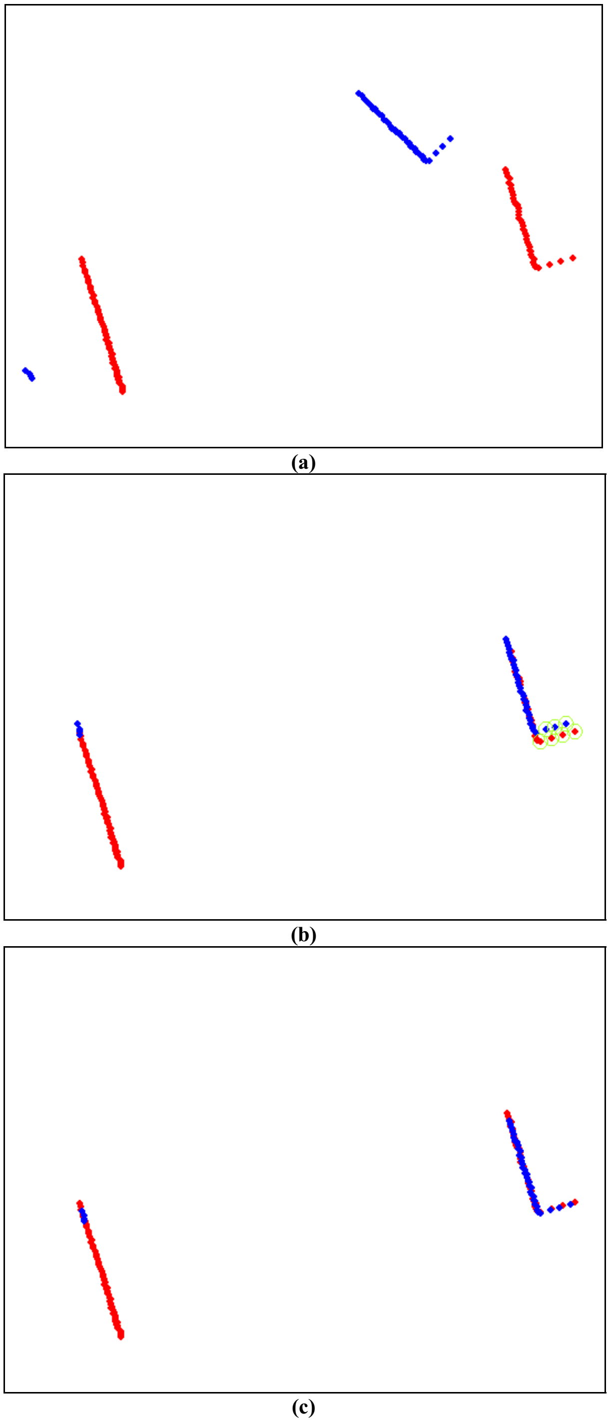


Fig.5. **Find Optimal Parameter.** (a) Raw laser scan data: L_{ref} (Red) and L_{scan} (Blue). (b) CVFSAC matching result. However, it is not optimal scan matching because of ignoring minimal secondary component (Green Circles). (c) Optimal scan matching is found by ICP correction.

4) Calculate translation of x-coordinate and y-coordinate of refined closest point pair.
5) Correct the translational error of scan matching parameter and Update scan data L_{scan}.
6) Iterative 2-6 while the Euclidean distance summation error of refined closest point pair has a minimum.

V. Acceleration Strategies

The main idea of the CVFSAC algorithm is already done in above sections. However, the CVFSAC algorithm is too slow to use for real-time mobile robot pose estimation. Because there are too many candidates of corresponding vector pair, and the ranking system is expensive to computation. Intuitively if laser scanner gets 361 range distance data array at once, than we need to search 361^2 candidates for find a best corresponding vector pair. So, let us introduce some strategies to reduce computational time.

■ Downsizing Numbers of Sampling

At first, we try to reduce numbers of corresponding vector pair candidate. We pick up only fine distributed vector of each laser data set since the fine distributed vector has high prior to be matched than others. The find distributed vector's definition is (*i) the length of measured distance is long than signal-to-noise ratio is high. (ii) The distance between measured position and follow position is close than the feature resolution is good.* Data in near the mean of distance between the measured position and followed one is satisfied these conditions (Fig. 6). Use mean and variance for this:

$$\bar{d} = \frac{1}{N-1}\sum_{i=1}^{N-1}\left\| d_i, d_{i+1} \right\|_E$$
$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - \bar{d})^2} \tag{8}$$

We experiment 0.2σ sample is good result and reduce much computation time than not using it.

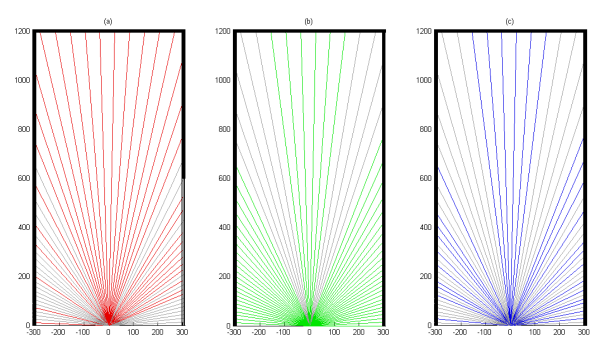


Fig.6. **Fine distributed vectors in MATLAB simulation**. (a) High SNR: Red Rays (b) Good Resolution: Green Rays (c) Combined two regions: Blue Rays

■ Region Limit by Course-to-fine Strategy

Matching region limitation can save time to find scan matching parameter. When the high matching scored pair is found we can do limits of search region of finding parameter.

■ **Region Limit Using Odometry**

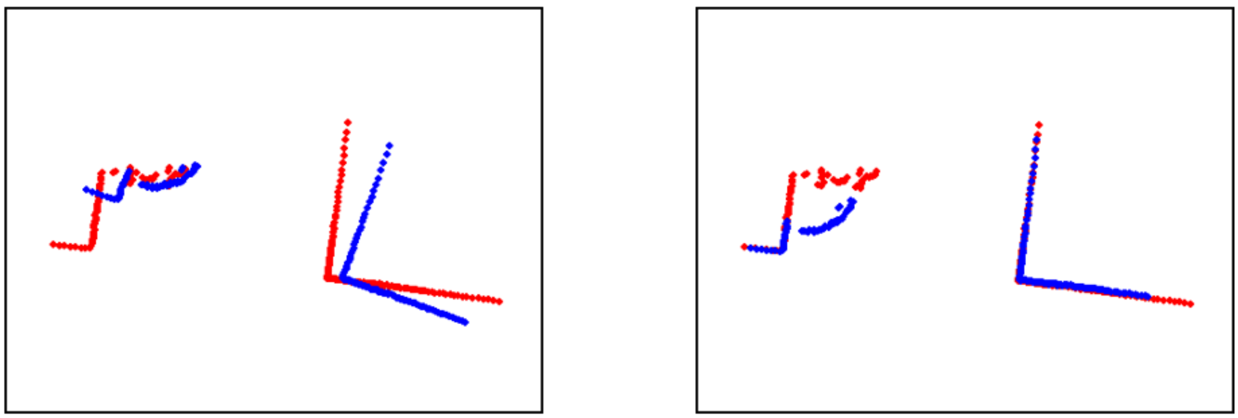
It is similar strategy as above. If we can set a possible scan matching region roughly we can ignore testing step before check the parameter candidate is out of region.

■ **Acceleration Using Parallel Computation Unit**

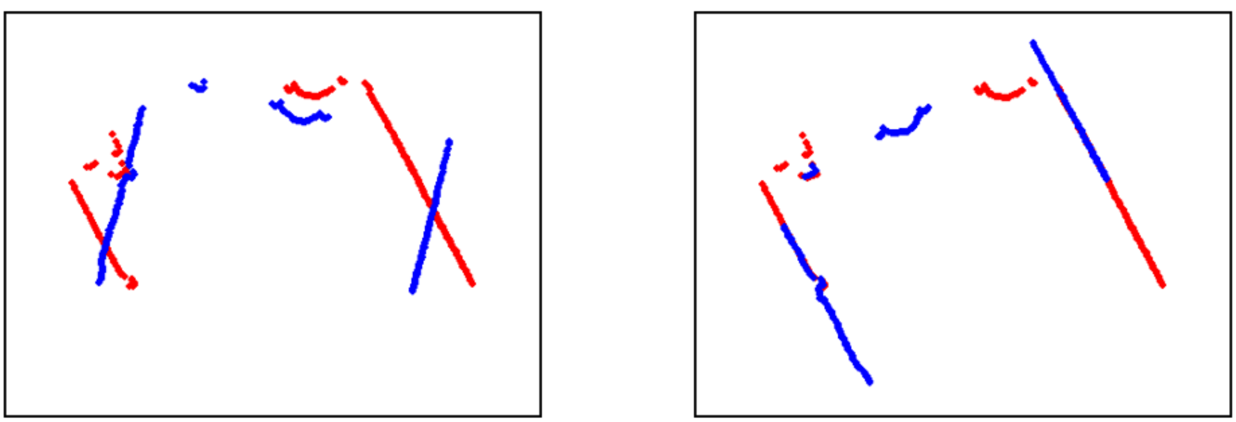
Our algorithm is not a type of iteratively update and find method but search-and-find sequence to achieve result. Parallel computation unit search all possible candidate at once.

VI. Experimental Results

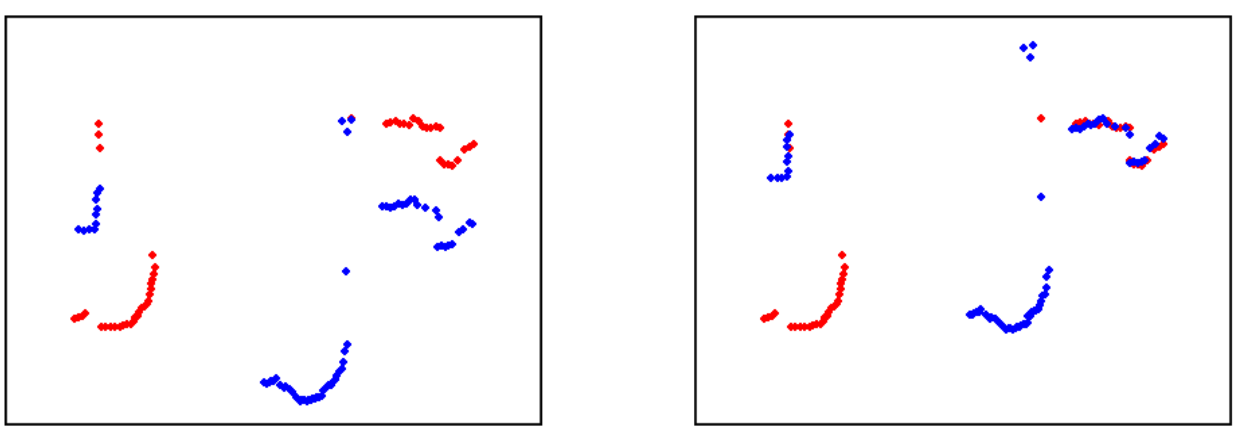
We experiment suggested method using two raw range data in dynamic environment. Left side images are raw laser scan data before matching and Right ones show after matched. Fig.7 (a) is indoor corner measured data L_{ref} and L_{scan} which have small moving object inside. Fig.7 (b) is a corridor data but more translated than Fig.7 (a). Fig.7 (c) is an outdoor trial. Fig.7 (c) has ambiguity what is static object or not. In this case we set region limit to matching it. All case appears reasonable matching result in dynamic environment.



(a)



(b)



(c)

Fig.7. **Experimental Results:** (a), (b) and (c) show laser scan matching by CVFSAC: (L_{ref} is red, L_{scan} is blue.)

VII. CONCLUSION

In this paper, we present a scan matching method, *Corresponding Vector Fitting SAC (CVFSAC),* for robot localization and map building. Our suggestion does not require feature extraction process and iteratively updating also not provide good initial position for matching. Our short experiment show positive performance in dynamic environment.

However, our algorithm has defects in high cost of testing step and possibility of wrong matching without any matching region limitation. For that reason we suggest you set proper computation and limitation strategy. These shortages are left as future problems. And Comparison of suggestion and a good scan matching algorithm Iterative Dual Correspondence (IDC) [17] and others reminds for future works.

REFERENCES

[1] Leonard, J.J. and Durrant-whyte, "Simultaneous map building and localization for an autonomous mobile robot", in *Intelligent Robots and Systems' 91.'Intelligence for Mechanical Systems, Proceedings IROS'91. IEEE/RSJ International Workshop on* , 1991, 1442–1447.

[2] F. Dellaert, D. Fox, W. Burgard, and S. Thrun, "Monte Carlo Localization for Mobile Robots", IEEE International Conference on Robotics and Automation (ICRA), 1999

[3] Montemerlo, M., Thrun, S., Koller, D. and Wegbreit, B., "FastSLAM: A factored solution to the simultaneous localization and mapping problem", Proceedings of the AAAI National Conference on Artificial Intelligence., 2002, pp. 593-598.

[4] Thrun, S., Burgard, W. and Fox, D., "*Probabilistic Robotics*", Cambridge: The MIT Press., 2005

[5] Yaqub. T. and Katupitiya. J., "Laser Scan Matching for Measurement Update in a Particle Filter", IEEE International Conference on Advanced intelligent mechatronics, 2007.

[6] Richard Hartley and Andrew Zisserman, *"Multiple View Geometry in Computer Vision"*, Cambridge University Press, 2004

[7] Joaquim Salvi, Carles Matabosch, David Fofi and Josep Forest, "A review of recent range image registration methods with accuracy evaluation", Image and Vision Compution, 578-596, 2007

[8] Paul J. Besl and Neil D. Mckay, "A Method for Registration of 3-D Shapes", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 4, no. 2, Feb. 1992.

[9] M. Tomono, "A scan matching method using euclidean invariant signature for global localization and map building", in *Proceedings of IEEE International conference on Robotics and Automation ICRA 2004*, vol. 1, 2004, pp. 866-871.

[10] Cox, I.J., "Blanche-an experiment in guidance and navigation of an autonomous robot vehicle", IEEE Transaction on Robotics and Automation, vol. 7, Apr. 1991, pp. 193-204

[11] G. Weiß and E. V. Puttkamer, "A Mapbased On Laserscans Without Geometric Interpretation", Intelligent Autonomous Systems, IOS Press, 2005, pp. 403-407

[12] Sharp, G.C, Lee, S.W. and Wehe D.K., "ICP Registration Using invariant Features", IEEE Transactions on PAMI, vol. 24, no. 1, Jan. 2002

[13] Rusinkiewicz, S. and Levoy, M., "Efficient Variants of the ICP Algorithm", Proceedings Third International Conference on 3-D Digital Imaging and Modeling 2001, 145-152

[14] Zhengyou Z., "Iterative point matching for registration of free-form curves and surfaces", International Journal of Computer Vision, vol. 13, Oct. 1994, pp. 119-152

[15] J. Minguez, L. Montesano, and F. Lamiraux, "Metric-based iterative closest point scan matching for sensor displacement estimation", IEEE Transactions on Robotics, vol. 22, no. 5, 1047-1054, 2006

[16] Diosi A. and Kleeman L., "Laser scan matching in polar coordinates with application to SLAM", IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005., 3317-3322, 2005

[17] F. Lu and E. Milios, "Robot pose estimation in unknown environments by mathcing 2D range scans", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR '94*, 1994

[18] Bengtsson, O. and Baerveldt, A.-J.," Localization in Changing Environments by Matching Laser Range Scans", 1999 Third European Workshop on Advanced Mobile Robots, Sept. 1999, pp. 169-176

[19] Dirk Hähnel , Dirk Schulz and Wolfram Burgard, "Mobile Robot Mapping In Populated Environments", Advanced Robotics, vol. 17, 2003

[20] C, Chen, Y. Hung. And J. Cheng., "RANSAC-Based DARCES: A New Approach to Fast Automatic Registration of Partially Overlapping Range Images", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, 1999, pp.1229-1234