

# A Novel Keep Zero as Zero Polar Correlation Technique for Mobile Robot Localization using LIDAR

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**Abstract**—Sensor fusion based localization techniques often need accurate estimate of the fast and uncertain scene change in environment. To determine the scene change from two consecutive LIDAR scans, this paper proposes a novel technique called ‘keep zero as zero’ polar correlation. As its name implies any zero in the scan data is kept isolated from scene change estimation as it does not carry any information about scene change. Unlike existing techniques, the proposed methodology employs minimization of selective horizontal and vertically shifted sum of difference between the scans to estimate scene change in terms of rotation and translation. Minimization of the proposed correlation function across the specified search space can guarantee an accurate estimate of scene change without any ambiguity. The performance of the proposed method is tested experimentally on a mobile robot in two modes depending on the scene change. In the first mode, scene change is detected using dynamic LIDAR, whereas static LIDAR is used in the second mode. The proposed methodology is found to be more robust to environmental uncertainties with a reliable level of localization accuracy.

**Index Terms**—correlation, mobile robots, pattern matching, sensor fusion, simultaneous localization and mapping.

## I. INTRODUCTION

Scene change estimation (SCE) is an important task in sensor fusion based localization algorithms [1]. An accurate SCE is important for reliable localization and consists of the following steps: environment scanning [2], feature extraction [3-4], data association [5-6] and estimate changes [7] in the associated feature. In SCE, errors introduced in feature extraction and association mismatch deteriorate the localization accuracy. The uncertainty and dynamic changes in environmental scenes due to appearance/disappearance of features from the robot’s vicinity compounds the SCE complexity further. Therefore, reliable feature extraction and data-association techniques are required for accurate localization.

Objective of this investigation is to propose a SCE algorithm that is more robust to the uncertainties in environmental features and computationally simple to be adapted in robots requiring run-time localization. The problem of SCE based localization has attracted significant research attention. The choice of sensors for various environments and techniques for various steps in SCE are

widely investigated. Exteroceptive sensors like Light incident detection and ranging (LIDAR) are used for environment scanning [7-8]. This is mainly due to their good sensitivity and fast scan rate [1].

Feature extraction algorithms filter environment scan data based on specific property (e.g., geometry [2, 5-6, 9]), to reduce the dimensionality of the map build using them. Hence, accuracy of the map very much depends on the feature selection criteria [10-11] and a wrong selection may result in loss of accuracy in the map. To overcome this challenge, adaptive [11], and graphical techniques [12-13] have been proposed for scan data selection. The feature maps thus obtained are associated using features available in common among them. Typically, association techniques in literature use geometric techniques [14-15] that are considered to be computationally cumbersome. Finally, the change in associated features is used to determine the changes in the scene.

A survey of existing literature reveals that the feature extraction techniques used will result in loss of scan data and the scene change information carried by them [11]. Association techniques with the reduced feature will result in multiple association possibilities and demands additional validation mechanism [16-18]. Therefore, existing association techniques, requires more iterations and increases complexity as the number of feature becomes large.

To overcome the existing challenges, the proposed work develops a robust and computationally fast SCE algorithm using a novel LIDAR based selective polar cross correlation technique. This method in a novel way determines the common features in the maps and employ cross correlation techniques to estimate the scene change in them. The cross correlation technique [19] involves minimization of mismatch between the consecutive maps by shifting within a bounded search space. Furthermore, by carefully studying the robot dynamics, the constraint in the search space can be determined in advance and which in turn can enhance the robustness of the proposed technique even amidst environmental changes.

Main contributions of this investigation are: (i) new filtering technique called keep zero as zero (KZZ) to filter the old/new features and to extract the common features from the LIDAR scans, (ii) cross correlation based

minimization algorithm over the specific search space for data association (iii) experimental set ups to validate the proposed technique to localize the mobile robot with sensor placed onboard as well as the sensor placed externally in a static mode.

The rest of the paper is organized as follows; Section 2 describes the problem formulation and presents the theory behind the sensor fusion based localization briefly. The formulation of the proposed KZZ correlation for SCE is presented in Section 3. Section 4 describes the methodology to evaluate the performance of the proposed SCE technique. The experimental results on a wheeled mobile robot to illustrate the performance of the algorithm are presented in Section 5. Finally the conclusion and the future prospects of this investigation are discussed in Section 6.

## II. PROBLEM FORMULATION

Typically, sensor fusion based localization [1] techniques employ two sensors namely, the odometer for state prediction and LIDAR for state correction. In state prediction, the robot wheel displacement is measured by the odometer and the past robot pose measurements are used to predict the current pose of the robot as in Fig. 1. This predicted robot pose is subjected to error due to wheel slip that is time-varying and complex to model. Hence, the predicted state has to be corrected using SCE between two successive LIDAR scans. The scene change between the scans are described by the relative rotation ( $\Delta\theta_s$ ) and translation ( $\Delta r_s$ ) which is numerically equal and opposite (see Fig. 2) of the robot pose change ( $\Delta R$ ) as in (1). Using this pose change the robot can be localized by defining the robot pose at the given time instant ' $t$ ' as in (2). The pose of a mobile robot ( $R_k$ ) is defined by its center position ( $x_{rt}, y_{rt}$ ) in a 2 dimensional space and its heading ( $\phi_t$ ).

$$\Delta R = \begin{bmatrix} \Delta\phi \\ \Delta r_r \end{bmatrix} = -1 \begin{bmatrix} \Delta\theta_s \\ \Delta r_s \end{bmatrix} \quad (1)$$

$$R_t = \begin{bmatrix} x_{rt} \\ y_{rt} \\ \phi_t \end{bmatrix} = \begin{bmatrix} \Delta r_r \cos \phi_{t-1} \\ \Delta r_r \sin \phi_{t-1} \\ \Delta\phi \end{bmatrix} + \begin{bmatrix} x_{rt-1} \\ y_{rt-1} \\ \phi_{t-1} \end{bmatrix} \quad (2)$$

This investigation proposes a SCE technique that uses KZZ horizontal cross correlation (KZZ-HXC) to determine the relative rotation ( $\Delta\theta_s$ ) between the present and past LIDAR scan. Next, the past scan is rotated using the estimated rotation [20] to align it with the present scan. Then the relative translation ( $\Delta r_s$ ) between these oriented scans is estimated using KZZ vertical cross correlation (KZZ-VXC) and finally using this estimated scene change the change in robot pose for state correction is calculated.

Let  $r_{s1}(n)$  and  $r_{s2}(n)$  be the two consecutive LIDAR scans acquired when the robot is at  $R_1$  and  $R_2$  poses respectively. The LIDAR scan is a discrete set of Euclidean distance of the obstacles from the robot center as in (3) over the entire span of scan area ( $[\theta_{\min} \ \theta_{\max}]$ ). The angles of the scanned obstacles ( $\theta_s$ ) are a set of monotonically increasing constants equal to the number of scanned data and calculated from its indices ( $n$ ) as in (4)

$$r_{st}(n) = \{r(n) | n \in [0 \ N_s], n \in \mathbb{Z}\} \quad t = 1, 2, 3.. \quad (3)$$

$$\theta_s = n\theta_{res} + \theta_{\min} \quad (4)$$

Where, the angular resolution ( $\theta_{res}$ ) of the LIDAR is given in (5)

$$\theta_{res} = (\theta_{\max} - \theta_{\min}) / N_s \quad (5)$$

The relationship between the local scans of the LIDAR can be defined in terms of relative robot pose as in (6),

$$r_{s2}(\theta_s) = f_{tr}(r_{s1}(\theta_s + \Delta\phi), \Delta r_r, \phi) \quad (6)$$

The translation function ( $f_{tr}$ ) in polar coordinate is given by (7) using the scan matrix ( $S$ ) and translation matrix ( $T$ ).

$$f_{tr}(r_s, \Delta r_r, \phi) = \sqrt{(S+T)(S+T)^T} \quad (7)$$

Where,

$$S = \begin{bmatrix} r \cos \theta_s \\ r \sin \theta_s \end{bmatrix}^T \quad \text{and} \quad T = \begin{bmatrix} \Delta r_r \cos \phi \\ \Delta r_r \sin \phi \end{bmatrix}^T$$

Thus, the proposed work aims to estimate the relative rotation ( $\Delta\phi$ ) and translation ( $\Delta r_r$ ) of the robot using scene change between the consecutive scans.

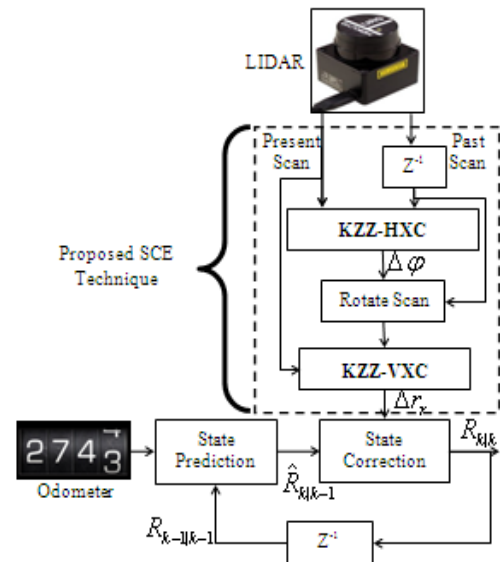


Figure 1. Proposed SCE in sensor fusion based localization framework

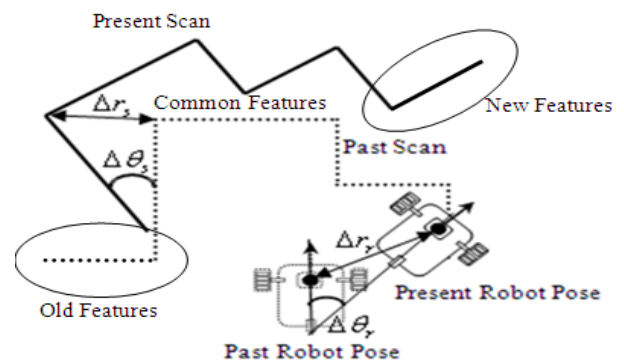


Figure 2. Scene change in LIDAR scans

## III. PROPOSED SCE METHODOLOGY

The scene change between the successive LIDAR scans can be determined by observing the relative changes between the associated features available in common between the scans. The relative changes are described in terms of rotation and translation between those common

features. Hence, the proposed SCE methodology uses two types of KZZ cross correlation technique namely (i) KZZ-HXC for rotation and (ii) KZZ-VXC for translation estimation respectively. Departing from the correlation techniques found in literature [21-23], the proposed method uses shifted sum of difference to calculate the correlation coefficients with the exception on zero values i.e. the zero in the range data will be discarded (kept aside) throughout the correlation operation. Hence the proposed technique is termed as 'Keep Zero as Zero (KZZ)' polar cross correlation.

#### A. SCE Operation

SCE is a three step process involving (i) identification, (ii) association and (iii) estimation of changes in the common features between successive scans. Two successive LIDAR scans have old, new and common features as shown in Fig. 2. In the SCE operation, the identification step involves the detection of common features among two successive scans using the proposed KZZ. The key idea of KZZ is a zero in the past scan and non-zero in the current scan indicates a new feature, whereas a non-zero in the past scan and a zero in the current scan indicate an old feature. The new features thus obtained do not have any common feature with past scan. Consequently, the old features are absent in the current scan. In the KZZ approach, common features among the two scans are identified by eliminating these new and old features that are not common in successive scans.

In the association step, the identified common features between the successive scans are associated using cross-correlation technique. It involves shifted matching of common features in present LIDAR scan with the static scan (i.e. past scan). The degree of association between common features is determined by calculating the cross correlation coefficient. Finally, to estimate the changes in the common features, the amount of shift required to associate the common features is computed by minimizing the cross-correlation coefficient. A minimum cross-correlation coefficient indicates an accurate matching between common features after retranslating the present scan.

The proposed correlation technique uses the polar coordinate [24] system wherein the horizontal axis represents the scan angle in degrees and the vertical axis represents the magnitude of obstacle range in meters. In the proposed KZZ-HXC, the magnitude of horizontal shift (scan rotation) required to match or align the two consecutive scans is used to estimate the robot rotation. Similarly, the magnitude of vertical shift (scan translation) required to match the scans is used to estimate the robot translation in KZZ-VXC. The horizontal shift will be uniform whereas the vertical shift uses a complex polar transform as in (6) using the robot heading ( $\phi$ ).

#### B. KZZ Horizontal cross correlation (KZZ-HXC)

The rotation angle between two LIDAR scans can be determined by minimizing KZZ horizontal cross correlation coefficient ( $H_c$ ) over the discrete search space ( $K$ ) as in (8). Unlike conventional technique, the search space is bounded as the relative rotation between the LIDAR scans are limited due to high scan rate of LIDAR. In the proposed

KZZ-HXC, a negative sign indicates that the scan is rotated anticlockwise (left shift) whereas a positive sign indicates a clockwise rotation (right shift) as indicated in Fig 3. The shifted scan will be zero padded to compensate for the length of the stationary scan ( $r_{s1}$ ). However, these padded zeros (new features) are not used in calculating the KZZ horizontal cross correlation coefficient ( $H_c$ ) using (9).

$$K = \{k \mid k \in [-N_s N_s], k \in \mathbb{Z}\} \quad (8)$$

$$H_c(k) = \begin{cases} \sum_{n=k}^{N_s} |r_{s1}(n) - r_{s2}(n-k)|, & k > 0 \\ \sum_{n=0}^{N_s+k} |r_{s1}(n) - r_{s2}(n+k)|, & k \leq 0 \end{cases} \quad (9)$$

Finally, using the calculated coefficient ( $H_c$ ) as a deviation metric for scan match (association), the magnitude of horizontal shift ( $k_{\min}$ ) to be compensated to match the scans is determined. The scan matching is indicated by a minimal value of  $H_c$  as in (10) over the search space.

Finally, the relative rotation ( $\Delta\theta_s$ ) is calculated using (11).

$$k_{\min} = \arg \min_k [H_c(k)] \quad (10)$$

$$\Delta\theta_s = \theta_{res} \times k_{\min} \quad (11)$$

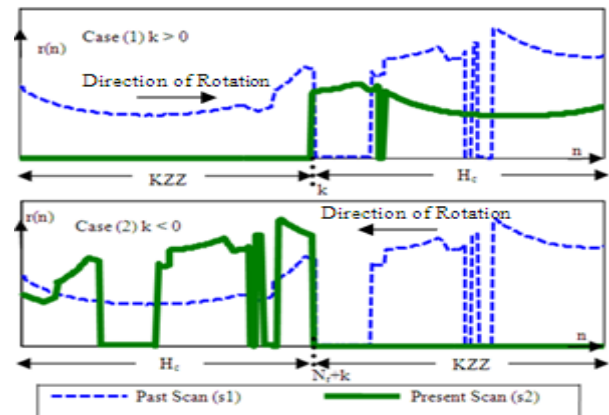


Figure 3. Illustration of KZZ-HXC

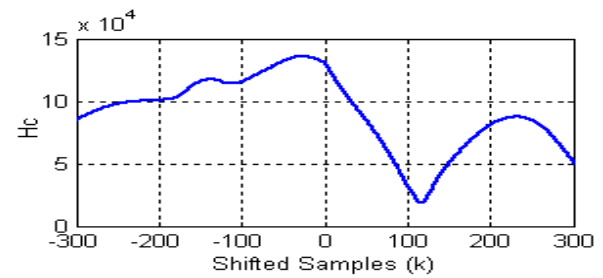


Figure 4. Horizontal cross correlation coefficient ( $H_c$ )

A bound in shifting sample size ( $k$ ) to calculate the correlation coefficient and usage of all the common features rather than a small set of features ensures global minima of  $H_c$  as illustrated in Fig. 4. A small set of features like corners, edges, line segments etc has been reported [3, 9, 11, 25] to be used for scene change estimation. This often results in complex and multiple iterations to associate and to determine scene change between those features. Thus, the proposed KZZ-HXC can able to estimate the relative rotation without any ambiguity within the bounded search

space.

### C. KZZ Vertical cross correlation (KZZ-VXC)

The present scan is rotated as in (12) using the estimated robot rotation in order to align both scans. Once the scans are aligned the deviations between them will be due to the translation alone. This relative change in translation ( $\Delta r_s$ ) can be estimated using the proposed KZZ-VXC. In this technique, the present scan data are vertically shifting (see Fig. 5) to match the past scan data using the complex transform as in (7). The match between the scans is indicated by minima in the vertical correlation coefficient ( $V_c$ ). Finally, the translation for which the vertical correlation coefficient is minimal indicates the robot translation.

$$r_{s2\theta}(n) = r_{s2}(n - k_{\min}) \quad (12)$$

$$L = \{l_s = lR_l \mid l \in [-S_l, S_l], l \in \mathbb{Z}\} \quad (13)$$

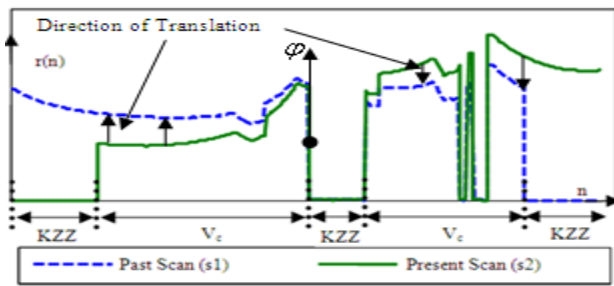


Figure 5. Illustration of KZZ-VXC

Unlike KZZ-HXC, the range vector ( $r_s$ ) of the LIDAR scans is in continuous space, hence the proposed KZZ-VXC is evaluated by using a user defined discrete translation search space ( $L$ ) as in (13). The span ( $S_l$ ) and resolution ( $R_l$ ) of the search space are defined by the user based on the speed and size of the robot platform respectively.

The KZZ based vertical correlation coefficient ( $V_c$ ) can be calculated using (14) for each element ( $l_s$ ) over this user defined search space ( $L$ ). The coefficient is calculated only in non-zero region ( $r_{s1}(n) \neq 0 \wedge r_{s2}(n) \neq 0$ ) which corresponds to presence of common features between both scans. The occurrence of new feature can be inferred by a non-zero region ( $r_{s1}(n) \neq 0 \wedge r_{s2}(n) = 0$ ) in present scan and a lost feature by non-zero region ( $r_{s1}(n) = 0 \wedge r_{s2}(n) \neq 0$ ) in past scan. These zeros are discarded in KZZ-VXC as constrained in (14). The proposed KZZ-VXC is illustrated in Fig. 7 and from which it is observed that the first part of KZZ infers about the addition of new features to the scan and last part indicates the loss of old features. However, both these regions don't participate in calculating  $V_c$ .

$$V_c(l_s) = \sum_{n=0}^{N_s} \left\| r_{s1}(n) - f_{tr}(r_{s2\theta}, l_s, \varphi) \right\| \quad (14)$$

$r_{s1}(n) > 0$   
 $r_{s2}(n) > 0$

The correlation coefficient is calculated by the absolute difference between the present and past scan for a particular magnitude of translation. Thus, a magnitude of translation

for which the correlation coefficient ( $V_c$ ) is minimal will result in the estimated robot translation as in (15). The variation of vertical cross correlation coefficient ( $V_c$ ) for the given local scans with respect to the applied translations is illustrated in Fig. 6. Unlike the horizontal cross correlation coefficient ( $H_c$ ), vertical cross correlation coefficient converges smoothly to minima which give the relative change in scans. This is due to existence of clear vertical space between the scans where as the horizontal space are distorted because of discontinuous features in the scans.

$$\Delta r_s = \arg \min_{l_r} [V_c(l_r)] \quad (15)$$

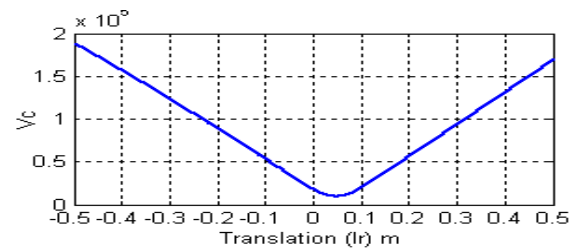


Figure 6. Vertical cross correlation coefficient ( $V_c$ )

## IV. PERFORMANCE EVALUATION

The proposed SCE technique is used to estimate the scene change between the successive LIDAR scans which can be used to determine the change in robot pose and to localize the robot. Hence, the performance of the SCE technique is evaluated in terms of its localization accuracy using mean average error (MAE) [26] as performance metric and its complexity in terms of its computation time for the given specifications.

The search space specifications for KZZ-HXC and KZZ-VXC technique are determined by the robot dimension and its navigation velocity as shown in Table I. For the given parameters, the MAE is calculated as arithmetic mean of the absolute error between the common features identified in the past scan ( $r_{s1}$ ) and the retranslated present scan ( $r_{s2\theta}$ ) as in (16). The present scan is retranslated using the estimated scene change estimated ( $\Delta\varphi_s$  in KZZ-HXC and  $\Delta r_s$  in KZZ-VXC) by the proposed SCE methodology as in (17).

$$r_{s2\theta} = f_{tr}(r_{s2}(\theta_s + \Delta\varphi), \Delta r_r, \varphi) \quad (16)$$

$$MAE = \frac{1}{N_s} \sum_{n=1}^{N_s} \left| r_{s1}(n) - r_{s2\theta}(n) \right| \quad (17)$$

$r_{s1}(n) > 0$   
 $r_{s2}(n) > 0$

Accurate scene change estimation can effectively retranslate the present scan such that it exactly aligns with the past scan and brings the MAE to a minimal value. This indicates a MAE between scans can able to validate the localization accuracy of the proposed SCE. Hence, the localization performance can be evaluated by benchmarking a threshold for MAE ( $A_l = 0.5686m$ ) which is maximum allowable deviation of the estimated robot pose from its actual pose.

The threshold ( $A_l$ ) is calculated by Euclidean distance of



the robot's top view (plan) dimension (Ref Table I) which in this particular experimental set up is a rectangular surface. The MAE below this threshold indicates that the rectangular surface of the estimated robot pose is in overlap with that of the actual robot pose and wider deviations have been observed if the MAE is above the threshold as shown in Fig. 7. This can be used to validate the proposed SCE to localize the robot using the estimated scene change between the present and past LIDAR scans.

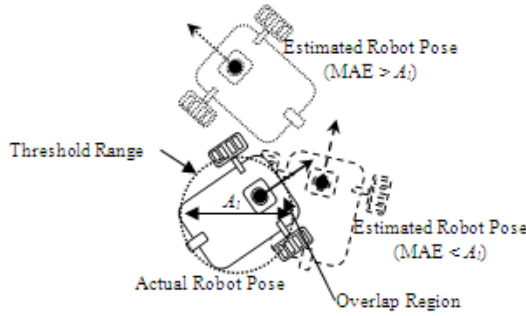


Figure 7. Illustration of threshold for localization accuracy

TABLE I. PARAMETERS FOR EXPERIMENTAL SETUP

Component	Parameter	Value
Mobile Robot (CoroBot-2WD)	Dimension	$0.47m \times 0.32m$
	Set Speed	$0.327 \pm 0.01m/s$
LIDAR (Hokuyo URG-04LX-UG01)	Scan Rate	0.2 sec/scan
	Angular Resolution	$0.352^\circ$
	Scan Area	$-30^\circ$ to $270^\circ$
KZZ-HXC	Search Space Index	$\pm 371$
	Search Space Range	$\pm 60^\circ$ per scan
KZZ-VXC	Search Space Span	50
	Search Space Resolution	0.05m
	Search Space Range	$\pm 0.25m$ per scan

The performance of the proposed SCE technique is evaluated in terms of its computational time which can illustrate the efficiency of the technique for real time implementation. The computational time taken by the proposed SCE is the sum of time taken to acquire the LIDAR scans and time taken for KZZ-HXC and KZZ-VXC algorithms. The experiments conducted with the given specifications (Ref Table. I) clearly shows that the average computational time for the KZZ-HXC to be 0.021s and for KZZ-VXC is 0.036s. This gives the total computation time to be 0.238s along with the LIDAR scan time of 0.2s. Only a small and acceptable variance in the computational time has been observed due to variations in common features present in each LIDAR scans as shown in Fig. 8. This illustrates the proposed SCE to be good enough for deployments requiring run-time localization.

## V. EXPERIMENTAL RESULTS

The performance of the proposed SCE is evaluated from experiments conducted using a two wheeled mobile robot (Coroware® – CoroBot-2WD) and Hokuyo® URG-04LX-UG01 type LIDAR with the specifications shown in Table I.

The algorithms are written on MATLAB® and executed in the robot's central processing unit (CPU) which has direct access to the robot hardware. The robot can be driven by manipulating the duty ratio of the Phidget® motor controller to control the robot wheel speed and direction. The duty ratio for individual wheels can be send from MATLAB® environment using Phidget® APIs. The robot can be operated and the performance of the proposed SCE can be visualized from a remote computer connected to the robot's CPU via remote connectivity using wireless network.

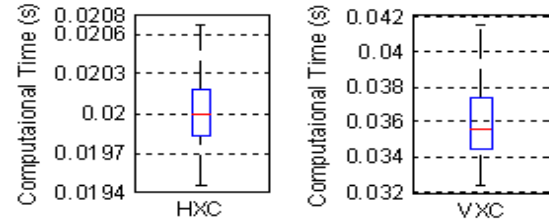


Figure 8. Computation time for proposed SCE technique

Two modes of experiments namely (i) Dynamic Scanner (DS) mode and (ii) Static Scanner (SS) mode are conducted. In both modes, the proposed SCE is used to estimate the scene change between the consecutive LIDAR scans as the robot navigates. MAE along with its threshold is used to estimate the localization accuracy. The number of LIDAR scans ('s') having MAE lesser than the threshold indicates the efficiency of the proposed technique.

### A. Experimental Setup-1 DS Mode

In DS mode, the proposed SCE is used to estimate the scene change between the local scans acquired from the LIDAR fitted on top of the mobile robot (see Fig. 9). The LIDAR communicates serially via USB port of the robot's CPU and sends the scan data along with the time stamp. The local scans are the maps of the environment with robot position as reference. The LIDAR position varies dynamically as the robot navigates creating a scene change between successive local scans. From the information that comes out of this scene change the robot pose can be estimated using the proposed SCE technique.

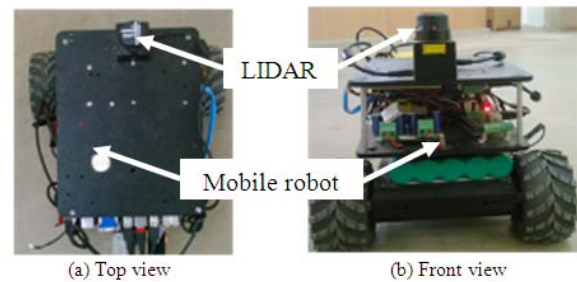


Figure 9. Mobile robot with LIDAR sensor

The performance of the proposed SCE technique is illustrated by its ability to retranslate the local scans using the estimated scene change. With the estimated scene change, the present scan is transformed accurately to match the past scan as illustrated in both polar and Cartesian coordinates (see Fig. 10). During experiments different conditions were tested considering the scenarios envisaged by the robot movement in an unknown environment and the

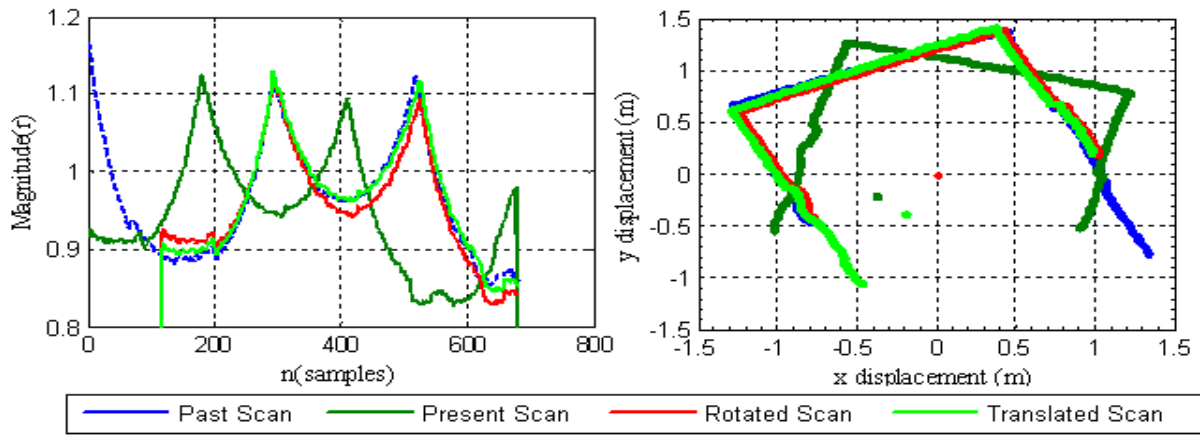


Figure 10. Scan matching in polar and rectangular coordinates

proposed SCE is employed to localize the robot and to retranslate the local scans. Three scenarios namely (1) rotation only (2) translation only and (3) both rotation and translation of robot are studied; these scenarios are exhaustive to capture all possible robot movements. The results illustrates that the MAE lies predominately well

below the threshold ( $A_r$ ) (see Fig. 11c) which indirectly demonstrates the localization accuracy of the proposed SCE. Acceptable level of deviations has been observed in the retranslated scans (see Fig. 11b) and the original map of the environment can be generated.

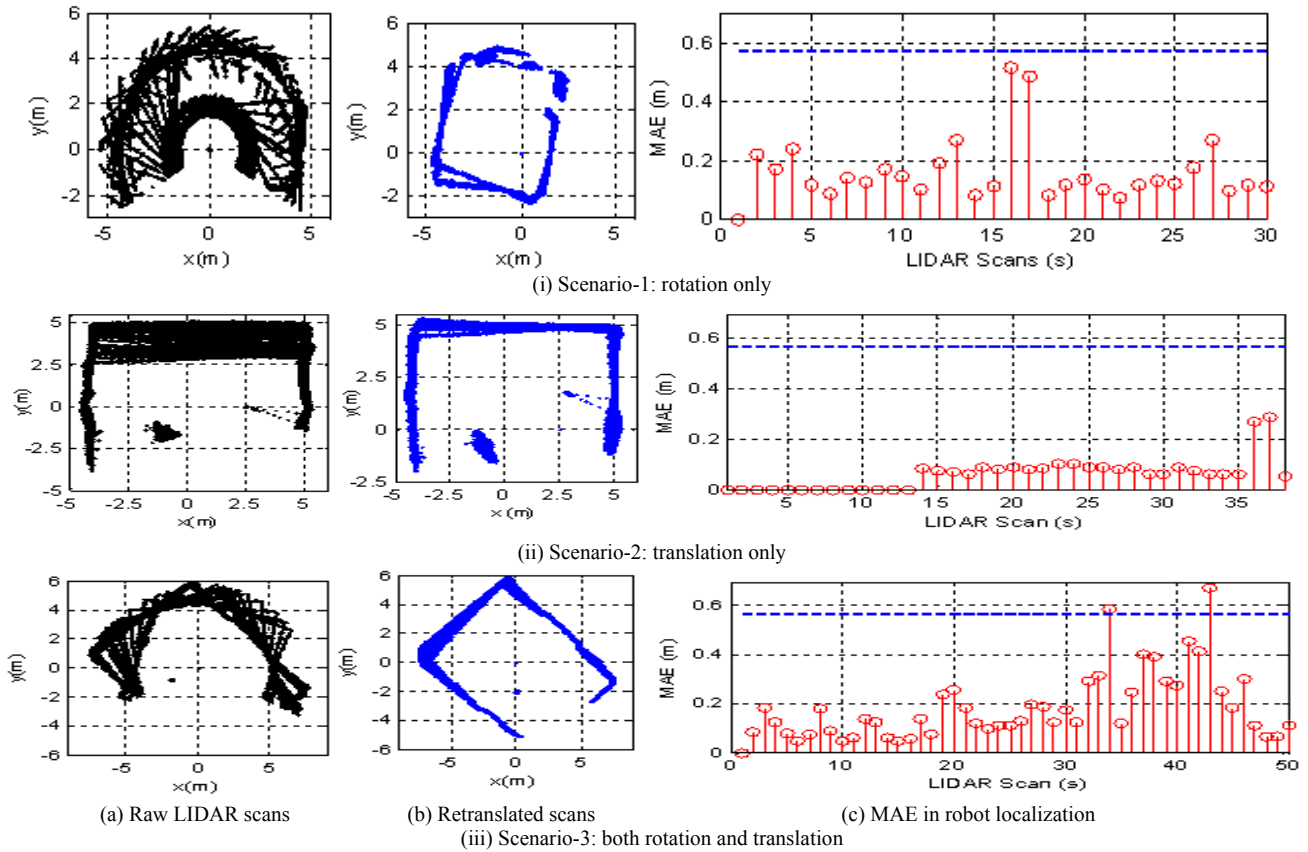


Figure 11. Localization and mapping using proposed SCE technique in DS mode

### B. Experimental Setup-2 SS Mode

In SS mode, the proposed SCE is used to estimate the robot pose using scans acquired from a static LIDAR kept in a known position which observes the changing pose of the robot as shown in Fig. 12. Unlike DS mode, the static LIDAR is connected to a laptop computer through the USB port. The proposed algorithm is executed in a MATLAB® environment on the laptop computer which can have access

to the LIDAR scan data. A test arena is designed to evaluate the performance of the proposed SCE technique in estimating the robot pose. The arena consists of three ranges of free space segmented as regions (1, 2 and 3) as shown in Fig. 13. Each region can be characterized by its depth of free space ( $r_{FS}$ ) over the LIDAR angle index ( $n$ ). The free space is the obstacles free region where the robot can possibly navigate. It is static and can be found out from the initial LIDAR scans.



Figure 12. Experimentation set up for SS mode

To localize the robot, the static LIDAR scan data which captures robot pose needs to be identified and isolated from the static environment data. In order to realize this isolation, the mobile robot is fitted with the identification marker block (cubic block) which in turn helps to identify the robot in the LIDAR scan data. The data associated with the obstacles in the environment will be selectively filtered out (set to zero) from the robot pose data using appropriate thresholds (see Fig. 13. green shades) derived from free

space ( $r_{FS}$ ) as in (18). Finally, the proposed SCE technique has been employed to this robot scan data ( $r_{st}$ ) to determine the robot pose change. The accuracy of the estimated pose change is evaluated by calculating the MAE between past and present robot scan data retranslated using the estimated pose change.

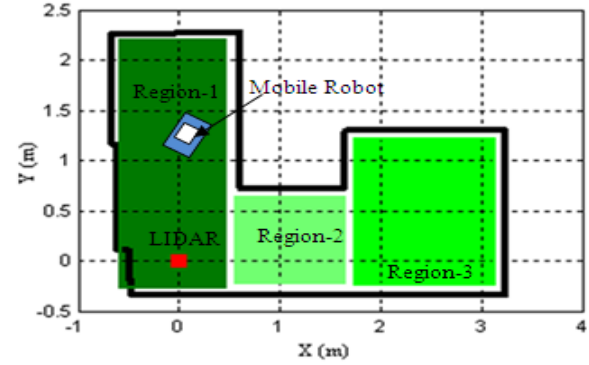


Figure 13. Test arena for SS mode

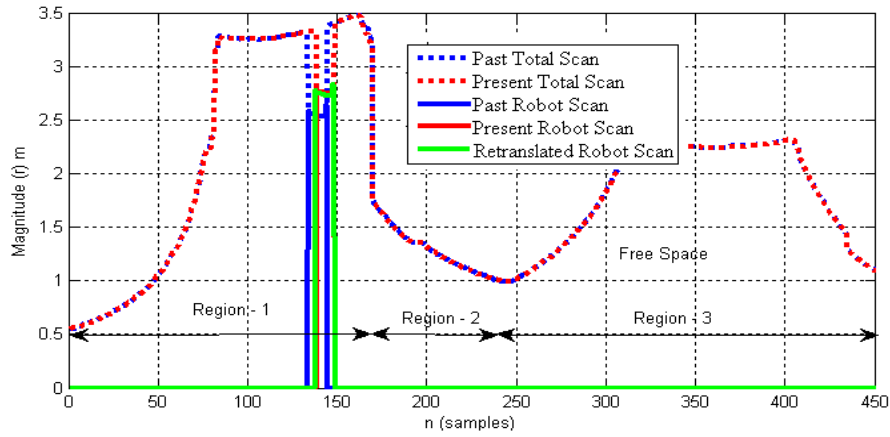


Figure 14. Isolation of robot scan data and its retranslation in SS mode

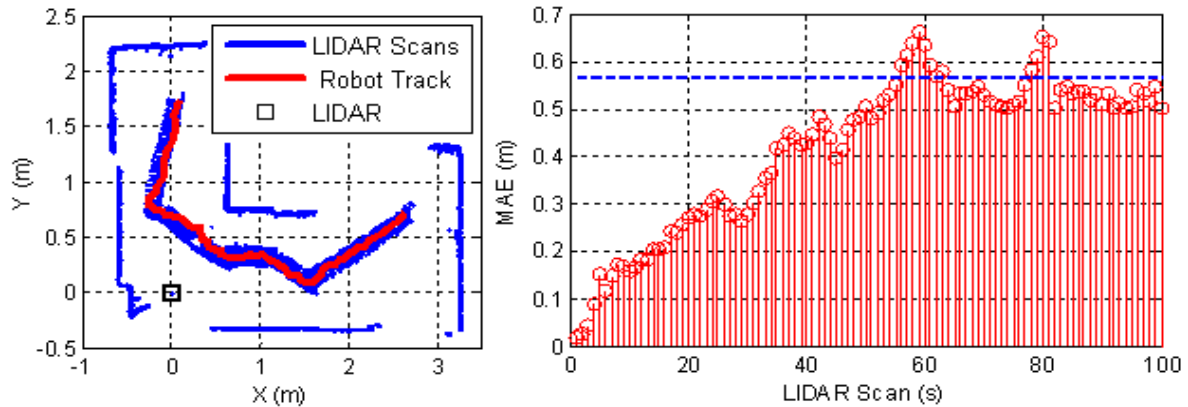


Figure 15. Tracking performance in SS mode

It is observed that the robot scan data is minimal in contrast with the environment scan data (see Fig. 14) which can reduce the computational time and also suffers loss of information. Hence the performance of the proposed SCE degrades in this mode compared with the DS mode. Figure 15 illustrates the performance of the proposed SCE technique to track the mobile robot navigating across all the three regions of the test arena. The MAE (see Fig 15b) calculated for each LIDAR scans can be used to evaluate the

tracking accuracy and it is observed that the proposed methodology is able to maintain the robot on track.

$$r_{st}(n) = \begin{cases} r(n) & |r(n) < r_{FS}(n) \\ 0 & |else \end{cases} \quad (18)$$

## VI. CONCLUSION

A novel KZZ polar correlation technique for SCE was proposed in this paper. It consists of a modified

conventional cross correlation technique called KZZ-HXC for rotation estimation and its extension to vertical axis called KZZ-VXC that was used for translation estimation. Unlike conventional cross correlation, the proposed technique used non-linearly shifted sum of selective difference between two LIDAR scan sequences which makes it an ideal tool for LIDAR based SCE. The accuracy and computational speed of the proposed cross correlation technique can be configured by proper selection of its search space. The performance of the proposed SCE is evaluated by computing the MAE between successive LIDAR scans (i.e. past scan and retranslated present scan). A threshold on the MAE value was used as a measure to evaluate the localization accuracy.

To evaluate the proposed methodology in localizing the robot in run-time, two sets of experiments were performed. The results showed that, in the DS mode, which uses environmental scene change acquired from a dynamic LIDAR and a MAE of 0.1851m per scan was observed during a combined rotation and translation movement of robot. Similarly, the robot scene change in the scans obtained from a static LIDAR using the proposed SCE to track the robot in SS mode, an average MAE of 0.4197m per scan was observed. These experimental results clearly demonstrated the efficiency of the proposed SCE methodology in various scenarios. Furthermore, the experiments showed that the computation time of the proposed SCE was quite suitable to localize the robot in run-time (see, Fig. 8); an advantage that promotes deployment of the localization algorithm in applications.

Combining the proposed technique with sensor fusion techniques employing extended Kalman filter or its variations for localization is the future prospect of this investigation.

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