Multisensor Fusion-Based Concurrent Environment Mapping and Moving Object Detection for Intelligent Service Robotics

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Abstract—Intelligent service robot development is an important and critical issue for human community applications. With the diverse and complex service needs, the perception and navigation are essential subjects. This investigation focuses on the synergistic fusion of multiple sensors for an intelligent service robot that not only performs self-localization and mapping but also detects moving objects or people in the building it services. First of all, a new augmented approach of graph-based optimal estimation was derived for concurrent robot postures and moving object trajectory estimate. Moreover, all the moving object detection issues of a robot's indoor navigation are divided and conquered via multisensor fusion methodologies. From bottom to up, the estimation fusion methods are tactically utilized to get a more precise result than the one from only the laser ranger or stereo vision. Furthermore, for solving the consistent association problem of moving objects, a covariance area intersection belief assignment is applied for motion state evaluation and the complementary evidences such as kinematics and vision features are both synergized together to enhance the association efficiency with the evidence fusion method. The proof of concept with experiments has been successfully demonstrated and analyzed.

Index Terms—Concurrent simultaneous localization and mapping (SLAM) and moving object detection, environment perception, multisensor fusion.

I. INTRODUCTION

INTELLIGENT robotic research is currently an increasingly important and significant topic. Due to the tremendous progresses in the sensing and computing technologies in recent years, the light detection and ranging (LIDaR) sensor, vision/omnidirectional camera, and stereo-based vision device have been mainly applied on intelligent robotic research works. The advantages of the LIDaR sensor, such as the laser ranger [6], are the high resolution and long distance, and the stereo-based vision device became more popular because of the lower cost benefit for both image processing and near-field depth measurement. Nowadays, various simultaneous localization and mapping (SLAM) methodologies have been derived and improved [1]–[3] with these perception sensors for mobile robot applications. Two aspects of the SLAM technique are as follows: feature-based SLAM [4] and graph-based SLAM [5]. Feature-based SLAM applies the estimation methods from Bayesian probability, and graph-based SLAM uses global optimal estimation techniques for relative observations.

SLAM methodology with path planning algorithms [9], [10] seems to achieve the autonomous navigation purpose in a static environment. However, three detection issues will be suffered when a service robot actually serves in a general indoor environment: 1) moving object or target perception in the vicinity of a service robot; 2) correct position estimation of the moving object with respect to the robot’s coordinate (this also implies that the motion of robot should be estimated); and 3) robust association when the moving object is occlusive or blanked. In related works, Glas et al. [11] and Chung et al. [12] proposed a laser-based human body track by the shape modeling for robot human following, i.e., these papers concern only human body extraction and estimation from the laser ranger. Bellotto and Hu [14] applied the laser ranger for human leg extraction and the vision camera for human face detection. The face information is fused to the legs' position using a sequential implementation of an unscented Kalman filter (UKF). That enhances the target estimation from the laser ranger and vision camera, but the SLAM problem was not concurrently taken into account. Cielniak et al. [13] have tried to integrate the indoor navigation problem on a Nomand-200 mobile robot. They used an appearance model of an artificial neural network from an omnidirectional camera for human target extraction; in addition, Kalman filter was utilized as a target tracker, but an extra indoor position system based on four fixed cameras should be pre-established. Wang et al. [15] have proposed a concurrent outdoor SLAM and moving object tracking (SLAMMOT) process via the dynamic Bayesian network as extended feature-based SLAM. However, the free-form object extraction (cars or pedestrian) from the laser ranger is only based on the distance/size criterion and without robust object association concern. Compared with previous works, we have developed and derived a new concurrent SLAMMOT from the graph-based SLAM, and all the moving object detection issues are divided and conquered via a synergistic strategy with multisensor fusion advantages.

Fig. 1 shows the flow diagram of this paper. In Fig. 1(a), first, a new augmented graph-based SLAM for concurrent robot postures and moving object trajectory estimation is described in
Section II. This augmented approach does not affect the original graph-based estimation method. Furthermore, for a convenient reference, we compared the time expense and accuracy performances of the global optimal estimation methods, namely, Tree-based netwORk Optimizer (TORO) and maximum likelihood estimator (MLE), with comments in Section VI-A. Fig. 1(b) shows the robot self-posture estimation unit that unites the wheel odometer and the iterative closest point (ICP) [16] alignment algorithm. In this part, ICP is applied as a sensor output between the relative laser ranger measurements, and the uncertainty model of the ICP is derived in Section III.

In this development, multisensor fusion and integration [7], [8] technologies are tactically adopted. In Fig. 1(c), when a target of interest (TOI) is extracted from the laser ranger, a predefined region of interest (ROI) will cover the TOI and map onto the stereo vision.

Scale-invariant feature transform (SIFT) [17], [18] matching is applied for stereo depth estimation. In Fig. 1(d), all the point estimations from the stereo vision and laser ranger can be fused by a covariance union (CU) [19], [20] technique to represent the whole object. Indeed, the covariance intersection (CI) [21] fusion technique is utilized to enhance the object estimation from the laser ranger and stereo camera. Fig. 1(e) shows the motion state evaluation after the object estimate result. A covariance area intersection (CAI) is proposed in Section V-B as a basic probability assignment (BPA) with Dempster–Shafer (DS) [22], [23] decision fusion for moving criterion. When a moving object is aware in the vicinity of a robot, the kinematics prediction and vision features are both integrated via DS evidence fusion again for moving object association enhancement, as shown in Fig. 1(f) and expressed in Section V-C. The experiment in Section VI-B exhibits the robust association result even if the moving object is temporary blanked in the sensor scope or suddenly changing their moving orientation. Finally, in Section VI-C, a completed concurrent SLAM and moving object detection result are demonstrated in an office building.

II. OPTIMAL ESTIMATION ON THE AUGMENTED RELATIONSHIPS

In this paper, the graph-based optimal estimation is proposed to augment the relationship between a robot and a moving object. From the optimal estimation, it is desirable to estimate the $n$-vector $\mathbf{X}$ modeled as an unknown parameter from the measurements of the $m$-vector $\mathbf{D}$. The linear equation can be stated as

$$\mathbf{D} = H\mathbf{X} + \mathbf{U}, \quad \mathbf{U} \sim \mathcal{N}(0; \sigma)$$

where $\mathbf{X}$ is the unknown parameter, $H$ is the association matrix, and $\mathbf{U}$ is the signal noise with Gaussian distribution. In graph-based SLAM, only the relative robot poses will be concerned and an innovative solution for concurrent SLAM and moving object trajectory estimation is derived by augmenting the relative observations between robot poses and object position, so that the optimal estimation can be applied not only for SLAM but also for the object trajectory. Consequently, the two problems can be accurately integrated into the same framework. Corresponding to the relationship of the robot and object estimation, $\mathbf{X}$ may represent the concatenation of actual robot postures $P_0, P_1, \ldots, P_n$ and object positions $O_1, O_2, \ldots, O_m$; $\mathbf{D}$ is the concatenation of all the relative observations; $H$ is the constraint matrix, and $\mathbf{U}$ is the observation uncertainty. The example can be described as follows:

$$\begin{bmatrix}
    d(P_0 \leftarrow 0) \\
    d(P_1 \leftarrow P_0) \\
    d(P_2 \leftarrow P_0) \\
    d(P_2 \leftarrow P_1)
\end{bmatrix} =
\begin{bmatrix}
    1 & 0 & 0 & 0 & 0 \\
    -1 & 1 & 0 & 0 & 0 \\
    -1 & 0 & 1 & 0 & 0 \\
    0 & -1 & 1 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
    P_0 \\
    P_1 \\
    P_2 \\
    O_1 \\
    O_2
\end{bmatrix}$$

$$+
\begin{bmatrix}
    d(O_1 \leftarrow P_0) \\
    d(O_2 \leftarrow P_0) \\
    d(O_1 \leftarrow P_1) \\
    d(O_2 \leftarrow P_2)
\end{bmatrix}$$
where $d(P_2 \leftarrow P_0)$ is the posture observation from $P_0$ to $P_2$ and $u(P_2 \leftarrow P_0)$ is the observation uncertainty. Applying the batch MLE [24] in this augmented expression, the robot and object pose in $X$ can be determined approximately as

$$X = (H^4C^{-1}H)^{-1}H^4C^{-1}D$$

$$C_x = (H^4C^{-1}H)^{-1}$$

where $C_x$ is the new covariance of the robot and object posture $X$ and $C$ is the covariance of observation $D$.

### III. ROBOT POSE ESTIMATE FROM ICP SCAN MATCHING

The ICP algorithm was developed by Besl and McKay [16] for shape registration applications. In this paper, the ICP result is proposed as a sensor output on pose estimation between the relative data acquisitions of the laser ranger. The error covariance evolution on the ICP alignment can be derived as follows:

$$Z = \{\rho_i, \theta_i\}$$

$$\rho_i = r_i + \varepsilon$$

$$P_i = (\rho_i \cos \theta_i, \rho_i \sin \theta_i)^T, \quad i = 1, \ldots, n$$

where $\rho_i$ is the range data, $\theta_i$ is the beam angle, and $\varepsilon$ is the random error with a Gaussian distribution $N(0, \sigma)$ of a laser ranger measurement $Z$. Let $I$ be the error function for ICP algorithm output as

$$I = \sum_i \| (R \cdot p^k_i + T) - \text{map}(R \cdot p^k_i + T, P^{k-1}) \|$$

where $k$ represents the frame or time index and the function $\text{map}(R \cdot p^k_i + T, P^{k-1})$ returns the closest points $p^k_j$ in the last model frame $k - 1$ for $p^k_i$. The ICP algorithm is applied to seek the pose transformation and rotation when the error function $I$ is minimized within a threshold, i.e., ICP arrives in a fit solution and a new pose increment $X$ (rotation and translation) is obtained. Under this condition, the uncertainty estimation of the new pose $X$ approximately depends on the minimized value $I$ and the covariance uncertainty is derived as

$$\text{cov}(X) \approx \left( \frac{\partial^2 I}{\partial X^2} \right)^{-1} \frac{\partial^2 I}{\partial Z \partial X} \text{cov}(Z) \frac{\partial^2 I}{\partial Z \partial X}^T \left( \frac{\partial^2 I}{\partial X^2} \right)^{-1}$$

where $\frac{\partial^2 I}{\partial Z \partial X}$ represents the implicit function theorem, which addresses the variation of the error function $I$ caused by measurement noise $\varepsilon$ from laser ranger measurement $Z$ in (4).

### IV. MULTISENSOR FUSION ON OBJECT ESTIMATION

#### A. Feature Extraction From Laser Ranger

For object discrimination purposes, the iterative end point fit (IEPF) [25] method is applied ahead from the laser ranger. After the ICPF, two constrained principles are added for the TOI extraction. One is segment size to filter out the huge object such as wall or furniture, and the other is the center-based nearest neighbor (CNN) criterion. The CNN criterion is a valid method to merge these pieced segments as a complete TOI candidate because the shape of a moving object such as human pose is time varying.

#### B. Feature Estimation From Stereo Vision

Two subprocesses of stereo vision are executed for this investigation. One is to fuse the laser measurements for the same object estimation, and the other is to enhance the moving object association which is described in Section V. From the stereo vision modeling [3], the world coordinates $(X, Y, Z)$ of a feature point can be computed from two matched points in the left and right images as

$$X = \frac{(c - c_0)b}{d} \quad Y = \frac{(r - r_0)b}{d} \quad Z = \frac{f b}{d}$$

where $(r_0, c_0)$ are the coordinates of the reference image center, $(r, c)$ are the coordinates of the key point in the reference image (the left one), $b$ is the baseline between the cameras, $d$ is the disparity, and $f$ is the focal length of both cameras. The errors in the variables $r, c,$ and $d$ are usually modeled as uncorrelated zero-mean Gaussian random variables with the variance $\sigma^2_r, \sigma^2_c,$ and $\sigma^2_d$. Using the first-order error propagation to approximate the distribution of the variables as multivariate Gaussians, the following covariance matrix can be obtained:

$$\Delta = \begin{pmatrix}
\sigma^2_X & \sigma^2_{XY} & \sigma^2_{XZ} \\
\sigma^2_{XY} & \sigma^2_Y & \sigma^2_{YZ} \\
\sigma^2_{XZ} & \sigma^2_{YZ} & \sigma^2_Z
\end{pmatrix} = J \text{ diag}(\sigma^2_r, \sigma^2_c, \sigma^2_d) J^T$$

where $J$ is the Jacobian matrix of the functions in (7) and $\sigma^2_X, \sigma^2_Y, \sigma^2_Z, \sigma^2_{XY}, \sigma^2_{XZ},$ and $\sigma^2_{YZ}$ are the variances and covariances of the corresponding coordinate variables.

When a TOI is extracted from the laser ranger, a ROI in 3-D space will be launched as a bounded box with the predefined parameters (height, width, and depth) for mapping onto the stereo images, as shown in Fig. 2(a) and (b). For the visual feature matching within the ROI, the scale invariant feature transform (SIFT) method is applied, as SIFT has emerged as an effective tool in general pattern recognition [17], [18]. The
horizontal lines represent the SIFT matched features, as shown in Fig. 2(c). With known paired camera parameters, all the matched features within the ROI will get the depth estimation by the stereo modeling in (7) and (8).

C. Object Estimation Fusion Using CU

In this part, the CU fusion method is utilized for the whole TOI estimation from the point measurements of the laser ranger and stereo vision. Given \( n \) point estimates represented as the mean and uncertainty variance \((P_{a_1}, a_1), (P_{a_2}, a_2), \ldots, (P_{a_n}, a_n)\), CU produces an estimate \((P_u, u)\) that is guaranteed to be consistent as long as the estimate \((P_{a_i}, a_i)\) is consistent

\[
P_a \geq P_{a_1} + (u - a_1)(u - a_1)^T, \\
P_a \geq P_{a_2} + (u - a_2)(u - a_2)^T, \\
\vdots \\
P_a \geq P_{a_n} + (u - a_n)(u - a_n)^T. \\
\]

(9)

The CU optimization constraints would be applied into a linear matrix inequality for a minimum-volume ellipsoid \(E_0\) containing \( k \) given ellipsoids. Each ellipsoid equation with a quadratic function such as

\[
E_i = \{ X \mid X^T A_i X + 2b_i^T X + C_i \leq 0 \}, \quad i = 0, \ldots, k.
\]

(10)

The minimum volume can be found by solving the following determinant maximization problems:

Minimize \( \log \det A^{-1} \)

Subject to :

\[
\begin{bmatrix}
A_0 & b_0 & 0 \\
\tilde{b}_0^T & -1 & b_0^T \\
0 & b_0 & -A_0
\end{bmatrix}
\begin{bmatrix}
A_0 & b_i & 0 \\
\tilde{b}_i^T & c_i & 0 \\
0 & 0 & 0
\end{bmatrix}
\leq 0
\]

\( i = 1, \ldots, k \)

(11)

where \( c_0 \) is given by \((c_0 = \tilde{b}_0^T A_0^{-1} b_0 - 1)\) [26]. The Maxdet problem is a convex optimization problem which can be efficiently solved by several algorithms, as discussed in [27]. The demonstrations of CU fusion from Fig. 2 are shown in Fig. 3. In Fig. 3(a), the blue ellipsoid shows the CU fusion result of the laser ranger uncertainty within the ROI. On the other hand, the green ellipsoid in Fig. 3(b) shows the 2-D mapping from the 3-D CU fusion result of the stereo vision estimate.

D. Object Estimation Fusion Using CI

In this part, the CI fusion method is utilized to enhance the same object estimation from the CU result of the laser ranger and stereo camera. Consider two different measurements \( A \) and \( B \) from different sources. Given the mean and variance: \( E\{A\} = a, E\{B\} = b, \text{var}\{A, A\} = P_{aa}, \text{var}\{B, B\} = P_{bb}, \)

\( \text{cov}\{A, B\} = P_{ab}, \)

define the estimate \( Z \) as a linear combination of \( A \) and \( B \) in the previous estimate of the same target with certain measurement uncertainty. The CI estimate output is defined as follows:

\[
z = P_{zz} \left( \omega_a P_{aa}^{-1} a + \omega_b P_{bb}^{-1} b \right)
\]

\( P_{zz} = \left( \omega_a P_{aa}^{-1} + \omega_b P_{bb}^{-1} \right)^{-1} \)

(12)

where \( \omega_a + \omega_b = 1, 0 \leq \omega_a, \) and \( \omega_b \leq 1. \) The parameters \( \omega_a \) and \( \omega_b \) modify the relative weights assigned to \( A \) and \( B. \) Different choices of the weights can be used to optimize the covariance estimate with respect to different performance criteria. In this paper, the minimal determinant cost function of \( P_{zz} \) is chosen. Let

\[
\omega_a = \omega, \quad \omega_b = 1 - \omega
\]

\[
\min_{\omega} \det \left\{ \left( \omega P_{aa}^{-1} + (1-\omega) P_{bb}^{-1} \right)^{-1} \right\}, \quad 0 \leq \omega \leq 1.
\]

(13)

This minimal definition reveals the nature of the optimality of the best \( \omega \) in the CI algorithm. In Fig. 3(c), the red solid ellipsoid shows the CI fusion result of the same object estimation from the laser ranger and stereo vision.
V. EVIDENCE FUSION ON MOVING OBJECT ASSOCIATION

The goal of moving object association is to decide whether a newly observed moving object corresponds to the existing moving objects or not. To solve this problem, two inferences with evidence fusion results are proposed. The first is to evaluate the motion state of the object, and the second is to associate between the existing moving objects.

A. DS Evidence Fusion

The evidence theory defined by Dempster and formalized by Shafer [22], [23] allows one to combine the evidence from different sources and arrive at a degree of belief that all the available evidences are taken into account. For different sources, the BPA does not refer to probability in the classical rule and it is possible to attribute an experiential mass function for a union of hypotheses. The description of the mass function can be represented by the following:

\[
m_n : 2^\Theta \to [0, 1]
\]
\[
m_n(\emptyset) = 0
\]
\[
\sum_{A \in 2^n} m_n(A) = 1
\]

(14)

where the frame of discernment \( \Theta = \{H_1, H_2, \ldots, H_n\} \) is composed of exclusive hypothesis and \( A \) is the subset of \( \Theta \). \( m_n \) represents the mass function of the power set \( 2^\Theta \) into the interval between 0 and 1. The new brief of subset \( A \) from two different mass briefs \( m_1 \) and \( m_2 \) is fused as

\[
m_1(A) \otimes m_2(A) = \frac{\sum_{A_i \cap B_j = A} m_1(A_i) \cdot m_2(B_j)}{(1 - k)}
\]

(15)

where \( k \) represents the basic probability mass associated with conflict.

B. Moving Detection of TOI

For moving detection, the easiest way is to subtract the adjacent measurements such as in the image processing. However, when the robot and object are both moving, it will mislead the result. The CAI criterion is used for TOI motion evaluation. If the covariance area \( T_i(k) \subseteq T_j(k-1) \) or \( T_i(k) \supseteq T_j(k-1) \), as shown in the two left panels of Fig. 4(a), the ith TOI in time \( k \) can be classified as a static object. The right panel of Fig. 4(a) shows a higher confidence for a moving object. The experimental BPA with an exponential parameter type is shown as in Fig. 4(b) where the \( x \)-axis represents the CAI percentage. The first inference is to decide the motion state of each current TOI as follows:

Motion state : \( \Theta = \{\text{Static} (S), \text{Dynamic} (D)\} \)

Subset : \( 2^\Theta = \{\emptyset, S, D, \Theta\} \)

C. Moving Object Association

When the motion state of current \( T_i(k) \) is decided as a moving object, i.e., \( m_i(D) > 0.5 \), and if \( T_i(k) \) is within the vision scope, then the SIFT features will also be recorded. The second inference combines kinematics prediction and vision features for moving object discrimination. Via the kinematics calculation, the next position of the current target can be predicted. Hence, the discrimination hypothesis can be defined as

\[
\text{Discrimination} : \Theta = \{\text{Identical} (I), \text{Nonidentical} (N)\}
\]

Subset : \( 2^\Theta = \{\emptyset, I, N, \Theta\} \)

The BPA : \( m_{ij}^s(\Theta) + m_{ij}^s(I) + m_{ij}^s(N) = 1 \)

(17)

where \( \emptyset \) represents empty and \( \Theta \) represents unknown state. The motion state of current \( T_i(k) \) is initialized with \( m_i(I) = 1 \). If \( T_i(k) \) has intersected with the last \( T_j(k-1) \), then the BPA of motion is given by CAI in Fig. 4(b). However, if \( T_i(k) \) has no intersection with the last \( T_j(k-1) \), then the maximum speed \( V_{\text{max}} \) of a moving object in the indoor environment is taken into account, so that the object maximum displacement \( d_{\text{max}} = V_{\text{max}} \cdot \Delta t \), where \( \Delta t \) is the sensor acquisition time interval. If the spatial distance between \( T_i(k) \) and \( T_j(k-1) \) is less than \( d_{\text{max}} \), then a dynamic assumption between \( T_i(k) \) and \( T_j(k-1) \) is assigned as \( m_{ij}(D) = 1 \).

\[
m_{ij}^s(I) = \rho_s \cdot \exp(-\alpha_s \cdot v_{ij})
\]

\[
m_{ij}^s(N) = \rho_s \cdot (1 - \exp(-\alpha_s \cdot v_{ij}))
\]

\[
m_{ij}^s(\Theta) = 1 - \rho_s
\]

(18)
where $\rho_s$ is the coefficient that characterizes the reliability of confidence from an evidence source, $\alpha_s$ is the normalized factor, and $v_{ij}$ is the information variation. For example, from the kinematics parameters, the position of the last target in the current time is predicted as $\hat{T}_j(k)$ and $v_{ij}$ is the distance variation between $T_i(k)$ and $\hat{T}_j(k)$. Moreover, $v_{ij}$ may also represent the visual matching ratio between $T_i(k)$ and $\hat{T}_j(k-1)$ from the SIFT features. By the DS fusion method in (15) again, the moving object association problem can be enhanced with the complementary evidences from kinematics prediction and vision matching.

VI. COMPARISON AND EXPERIMENTAL RESULTS

A. Comparisons of Optimal Estimation Method

The optimal estimation usually applies some elimination techniques to reduce the optimization process. The popular solutions in minimizing the error defined by the observation constraints are iterative optimal approaches or the artificial particle swarm optimization [28], [29]. In this paper, the MLE is compared with the TORO [30]. Fig. 5(a) shows the simulation of a robot trajectory as ground truth from posture ($x = 0$; $y = 0$; $\theta = 0$). There are 144 robot postures (black nodes) recorded in every 50 cm of displacement, and all the nodes are restricted to the adjacent edge association from the previous nodes.
Also, the adjacent estimate uncertainty is assumed as Gaussian with translation deviation of 5 cm and rotation deviation of 0.5°. Fig. 5(b) shows the odometerlike result of robot posture estimation with the accumulated uncertainty error with respect to the simulated ground truth. Fig. 5(c) shows the optimal alignment after MLE.

From the comparison in Fig. 6, the computational time expense of TORO (with the fixed iterations 20 ∼ 100) nears a constant proportion with the dimension of the constraint matrix and MLE nears an exponential growth with the matrix dimension. However, the alignment precision of MLE is always better than that of TORO. This can be a tradeoff between time efficiency and alignment accuracy when applying the graph-based optimal estimation process. In this simulation, when the dimension of the constraint matrix is less than 1200 (nodes and edges), the MLE performance is better than the optimal TORO runs in 100 iterations.

B. Moving Object Association by Evidence Fusion

The association problem is demonstrated here when people walk shoulder to shoulder and then suddenly depart when changing their travel orientation. This is a common scene when people are walking in an indoor environment. Fig. 7 shows a male and a female walking toward the robot, and the SIFT features are captured in the ROI (left camera) from time stamp 2 to time stamp 8 (the sensing interval is 0.5 s). Fig. 8(a) shows the sequence position of moving object estimate, and the blue line represents the kinematics prediction. Fig. 8(b) and (c) represents the correct trajectory after the inference fusion result.

In time stamp 2, two moving objects are identified. In time stamp 3, four associated assumptions (the arrow symbols in Table I): \( T_i(t = 3)|i = 1, 3 \) map to last object \( T_i(t = 2)|i = 1, 3 \). Regardless of kinematics or SIFT belief confidence, the \( T_1(3) \) (male) is highly identified to \( T_1(2) \) with the maximum fusion confidence of 94%. However, in time stamp 4, the male suddenly changes his orientation and obstructs the view of the female. Thus, only one object is of concern and the kinematics assumption beliefs for \( T_1(4) \) from \( T_1(3) \) and \( T_2(3) \) are 37% and 31%, respectively. Now, it is rather more difficult to decide the real association of \( T_1(4) \). However, accompanied with the SIFT belief, \( T_1(4) \) still has 83% fusion confidence to associate with \( T_1(3) \). In time stamp 5, both female and male are detected again by the laser and vision and the male \( T_2(5) \) is associated to \( T_1(4) \) with the 89% fusion confidence. The female \( T_1(5) \) is now a newly detected target with unknown status. Thus, a nearest previous association is triggered. In Table I, \( T_1(5) \) is associated with the previous \( T_3(3) \) with a maximum fusion confidence of 86% from kinematics and SIFT beliefs.

C. Concurrent SLAM and Moving Object Detection

The scenario of concurrent SLAM and moving object detection is demonstrated here for a routine indoor patrol task of an intelligent service robot. Fig. 9(a) shows the static environment map construction result of an office building. There are 49 laser reference frames created when the service robot executes a round trip (the red trajectory) in the space roughly 30 m × 25 m, as shown in Fig. 9(b). Fig. 10 shows the concurrent robot postures and moving object trajectory estimation results. The moving object will be filtered out, and the 49 static reference frames in Fig. 9 are enough for robot self-pose association and localization. In time stamp 6, the first moving object is identified near the toilet entrance and the robot is controlled to follow behind. In time stamp 45, the second moving object is also detected near the downward stairs, but in time stamp 62, object 1 is blanked by object 2. In time stamp 63, a new object is detected and associated correctly to the previous moving object 1. The third moving object is identified in time stamp 68 and blanked by object 1 in time stamp 72. Also, in time stamp 73,
the new object is associated with the previous moving object 3 again. In time stamp 185, the robot finishes the security patrol task and all the trajectory discriminations of the moving object are shown correctly.

VII. CONCLUSION

This paper has presented the synergy of the multisensor fusion development that focuses on the environment perception and navigation of an indoor service robot. The major contributions of this research are as follows. A new augmented approach of graph-based SLAM is derived for concurrent robot postures and moving object trajectory estimate. Moreover, the time expense and global accuracy of the TORO and the MLE are compared with a choice comment: The TORO method performs well in time efficiency for a large dimension of constraint matrices such as in an outdoor or urban environment, but in the indoor or general office building, the MLE process is better for global accuracy than TORO with an acceptable computation time.

The moving object detection issues of a robot’s indoor navigation are divided and conquered via multisensor fusion methodologies. From bottom to up, the measurement uncertainties of robot sensors have been intensively investigated by applying the CU fusion method, and the CI method is tactically employed to fuse the CU results for a more accurate estimate than the one from only the laser ranger or stereo vision camera. For consistent moving object association, two inferences and fusion verification are proposed. First, the CAI is converted to a belief function for evaluating the motion state of the TOI. Second, the kinematics prediction and vision features will also serve as complementary evidence. By applying the DS method, the experimental and comparative results have exhibited the correct trajectory of a moving object in a general indoor environment, even if the moving object is temporarily blanked in the sensor scope or they suddenly change their moving orientation. Finally, the concurrent SLAM and moving object detection are completely demonstrated in an office building environment.

REFERENCES


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