Data Association in Dynamic Environments Using a Sliding Window of Temporal Measurement Frames

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Abstract— **Correct data association is critical for the success of feature based simultaneous localization and mapping (SLAM) of autonomous vehicles or mobile robots. Incorrect associations result in map inconsistency and inaccurate path estimates. Numerous data association techniques proposed in the literature for SLAM assumes a static environment. Ignoring the effects of moving or dynamic objects leads to catastrophic failures. This work, proposes a new multiple frame batch temporal consistency criterion for data association in feature based SLAM in dynamic environments. Simulations and experimental results are presented to demonstrate the effectiveness of the algorithm.**

Keywords-tracking; – **localization, mapping**

I. Introduction

After nearly one and half decades of extensive research, simultaneous localization and mapping (SLAM) is still considered as one of the fundamental and main challenges in achieving autonomous navigation capabilities. A SLAM algorithm in a nutshell attempts to build an environmental representation (called a map) and at the same time determine the robot's pose in the map. SLAM finds numerous applications in military reconnaissance, surveillance, under water exploration, planetary exploration, mining, cargo handling, surveying and driver assistance systems. One of the inherent attributes of SLAM is its correlation between map elements and the platform pose [1], [2]. Self and Cheeseman [1], were the first to emphasize the importance of maintaining map and vehicle correlations in SLAM. Maintaining map-vehicle correlations gives rise time quadratic state estimation complexity and an exponential search space for data association. Self and Cheeseman introduced the widely popular extended Kalman filter (EKF) based SLAM algorithm, which is used to estimate the robot's pose and the feature coordinates defining the map simultaneously in a composite state vector. The work in [1] stimulated considerable interest among the robotics community and was followed by the work of Mourtarlier and Chatila [2], Ayache and Faugerras [3] on visual navigation and more recently, probabilistic and particle filter based methods [4], [5] and [6]. In this work, we consider the estimation theoretic feature based SLAM framework [1] using EKF. The EKF based SLAM has several shortcomings. More specifically, the inconsistent treatment of nonlinearities and data association ambiguities that often result in poor filter performance leading to incorrect localization results and map divergence.

The data association problem is often considered as one of the most difficult problems in state estimation and in particular in SLAM. The data association problem in SLAM [7] tries to establish correspondence among landmarks or features in the state vector and that of the observed landmarks (or measurements) before state update. Data association problem in SLAM is difficult even in static environments and much more challenging in dynamic environments. Large uncertainties in vehicle pose, varying feature densities, false alarms and occlusion complicate the data association problem in SLAM on various counts. In multiple target tracking from a stationary sensor, when the targets move independently from each other, the sensor measurements of targets are not correlated. Therefore likelihood of observing one target is independent of the likelihood of observing another. However this is not the case in SLAM where the features are correlated with each other and with the robot pose. In addition, measurements are also correlated with each other. Consequently, the simplest of all, the nearest neighbor data association algorithm, often yield false matches and hence inconsistent and divergent localization results. Joint Compatibility Branch and Bound (JCBB), [9] and Combined Constrained Data Association [8] are well known batch data association schemes which take correlation into account implicitly by considering batches of target measurement pairs in the association process. However the relatively higher complexity of these algorithms and their search in one frame of measurement do not make them useful in large outdoor terrains which consist of a multitude of features and dynamic objects such as moving vehicles and people. Further, there is a high chance of clutter or measurements of dynamic objects having compatible pairs with all the other features giving rise to false matches. One possibility is to detect and exclude dynamic objects before data association is carried out or simultaneously track the dynamic objects [11]. This introduces additional complexity to the problem.

The presence of dynamic objects in the environment violates the static map assumption in standard SLAM. Also the presence of dynamic objects (eg pedestrians, animals, cars, buses and bicycles etc.) with varying sizes and moving at varying speeds make the feature extraction process complex and error prone. There is also a high probability of interpreting temporarily static objects such as vehicles stopped at traffic lights as static objects. Thus, if we are to deploy autonomous platforms running SLAM algorithms in dynamic environments [11] there should be proper means of filtering out moving objects from the static objects. Further, the data association problem becomes difficult by occlusion and clutter as a result of dynamic objects. Experiments in crowded environments show significant increase in false alarm rates and a rise of false matches therein. This paper proposes a new algorithm to overcome these problems.

The paper is organized as follows. In Section II a general window based formulation of multiple frame assignment is presented for delayed data association decision making. Section III includes a summary of SLAM and the delayed multiple frame data association approach for SLAM and methods of traversing this multi-dimensional search space in an efficient manner. Section IV verifies the framework and algorithm developed using simulations and experimental results obtained from implementing SLAM algorithms in neighborhood environments and Section V presents conclusions and future work.

II. A General Framework for Delayed Data Association

A. General Multiple Frame Formulation

A windowed version of generalized data association framework is formulated in this section for robot navigation tasks. Suppose that there are N frames of measurement, $frame_{k-N+1}$, $frame_{k-N+2}$, $frame_{k-N+3}$, .. , $frame_{k-1}$, and $frame_k$, obtained at time instances, $k-N+1$, $k-N+2$, $k-N+3$, …, $k-1$, and k respectively, are available over a period of time, $[k-N+1, k]$. Let $\mathbf{Z}(k-N+1)$, $\mathbf{Z}(k-N+2)$, ….. , $\mathbf{Z}(k-2)$, $\mathbf{Z}(k-1)$ and $\mathbf{Z}(k)$ be the sets of measurements obtained in $frame_{k-N+1}$ up to $frame_k$ and $\mathbf{Z}(l) = \{\mathbf{z}_{i_l}(l) \mid i_l = 0,1,2........,n_l\}$ for all $l = k-N-1,\ N-2, ..., k-1,\ k$. Here n_l is the number of measurements obtained in frame l. Let $\mathbf{z_0}(k-N+1)$, .., $\mathbf{z_0}(k)$ denote dummy or fictitious measurements used to accommodate the missed detections of tracks in the respective measurement frames, so that tracks not detected in the frames concerned could be assigned to them.

Let T^S denote, a partition of assigning T, existing features, ($\Gamma = \{\tau_t \mid t = 1,2........,T\}$) to the available measurements in the N consecutive measurement frames. In other words, T^S is a partition of $\Theta = \mathbf{Z}(k-N+1) \times \mathbf{Z}(k-N-2) \times ...... \times \mathbf{Z}(k) \times \Gamma$. Now, the solution to the multiple frame data association problem can be formulated in general as a discrete optimization problem minimizing a given cost function, C_Θ relating the measurements in N frames to T targets subject to an appropriately chosen set of constraints.

$$\Phi_N = \min \ C_\Theta(\Gamma, \mathbf{Z}(k-N+1), ..., \mathbf{Z}(k-1), \mathbf{Z}(k), \Theta_\eta) \tag{1}$$

Where, Θ_η consists of binary variables $\eta(t, i_{k-N+1}, i_{k-N+2}, ..., i_k) \in \{0,1\}$ such that $t \in \{1,2,..,T\}$ and $i_{k-m} \in \{0,1,2,....,n_{k-m} \ for \ m = N-1, N-2, ..., 1, 0\}$. Here $\eta = 1$ indicates that the measurement sequence $\mathbf{z}_{\mathbf{i}_{k-N+1}}(k-N+1)$, $\mathbf{z}_{\mathbf{i}_{k-N+2}}(k-N+2)$, ……., $\mathbf{z}_{\mathbf{i}_{k-1}}(k-1)$, and $\mathbf{z}_{\mathbf{i}_k}(k)$ in N frames of measurement, $frame_{k-N+1}$, $frame_{k-N+2}$, $frame_{k-N+3}$, ……….. , $frame_{k-1}$, and $frame_k$ respectively is associated with the target τ_t. Also η can be determined from,

$$\eta = \arg \min_{\eta} \ C_\Theta(\Gamma, \mathbf{Z}(k-N+1), ..., \mathbf{Z}(k-1), \mathbf{Z}(k), \Theta_\eta) \tag{2}$$

The problem (1) is inherently NP hard and suboptimal solutions have to be used in practice. The nature of this problem depends on several factors. As such the selection of the cost function, independence of measurements and the number of measurement frames affect the solution of this problem and complexity. Further, it is customary in tracking community to constrain and pre-process the association space, to reduce complexity. An analysis of the problem shows that, it is easy to arrive at the following constraints, significantly limiting the search space:

1) Assuming that each measurement is a result of a single landmark we have the single source constraint for measurements:

$$\sum_{i_{k-N+2}=0}^{n_{k-N+2}} .... \sum_{i_k=0}^{n_k} \sum_{t=1}^{T} \eta(t, i_{k-N+1}, ..., i_{k-1}, i_k) \le 1, \ i_{k-N-1} = 1,2,...,n_{k-N+1} \tag{3}$$

$$\sum_{i_{k-N+1}=0}^{n_{k-N+1}} ..... \sum_{i_{k-m-1}=0}^{n_{k-m-1}} \sum_{i_{k-m+1}=0}^{n_{k-m+1}} .... \sum_{i_k=0}^{n_k} \sum_{t=1}^{T} \eta(t, i_{k-N+1}, ..., i_{k-1}, i_k) \le 1 \tag{4}$$

$$i_{k-m} = 1,2,....,n_{k-m} \ , m = N-2, N-3,..,1$$

$$\sum_{i_{k-N+1}=0}^{n_{k-N+1}} .... \sum_{i_{k-1}=0}^{n_{k-1}} \sum_{t=1}^{T} \eta(t, i_{k-N+1}, ..., i_{k-1}, i_k) \le 1, \ i_k = 1,2,....,n_k \tag{5}$$

2) Since one landmark is assumed to have only one return at an instant we have the single return constraint:

$$\sum_{i_{k-N+1}=0}^{n_{k-N+1}} .... \sum_{i_k=0}^{n_k} \eta(t, i_{k-N+1}, ..., i_{k-1}, i_k) = 1, \quad t = 1,2,....,T \tag{6}$$

3) The maximum number of missed detections in a frame of measurements is assumed to be less than or equal to the number of landmarks present at that instance hence giving a constraint on maximum number of dummy measurements:

$$\sum_{i_{k-N+2}=0}^{n_{k-N+2}} .... \sum_{i_{N-1}=0}^{n_{k+N-1}} \sum_{t=1}^{T} \eta(t, 0, ..., i_{k-1}, i_k) \le T \tag{7}$$

$$\sum_{i_{k-N+1}=0}^{n_{k-N+1}} .. \sum_{i_{k-m-1}=0}^{n_{k-m-1}} \sum_{i_{k-m+1}=0}^{n_{k-m+1}} ... \sum_{i_k=0}^{n_k} \sum_{t=1}^{T} \eta(t, i_{k-N+1}, .. i_{k-m-1}, 0, i_{k-m+1}, .., i_k) \le T \tag{8}$$

$$, m = N-2, N-3,..,1$$

$$\sum_{i_{k-N+1}=0}^{n_{k-N+1}} ... \sum_{i_{k-1}=0}^{n_{k-1}} \sum_{t=1}^{T} \eta(t, i_{k-N+1}, ..., i_{k-1}, 0) \le T \tag{9}$$

4) Since η is an association variable, η must be either 0 or 1 and hence:

$$\eta(t, i_{k-N+1}, ..., i_{k-1}, i_k) = (0,1),\ \forall i_{k-N+1}, i_{k-N+2}, ..., i_k, \quad t = 1,2,...,T \tag{10}$$

B. Implications in SLAM

In multiple target tracking, from a stationary sensor, and when targets move independently, sensor measurements are not correlated. Then it is possible to calculate individual likelihoods of measurement to target associations separately for each target measurement pair. If the likelihood of assigning *T* targets to measurements in *N* frames is used in the above formulation as the cost function, the data association problem reduces to a nonlinear 0-1 integer program of the following form:

$$\text{Minimize} \quad \sum_{i_{k-N+1}=0}^{n_{k-N+1}} \sum_{i_{k-N+2}=0}^{n_{k-N+2}} \cdots\cdots \sum_{i_k=0}^{n_k} \sum_{t=1}^{T} \eta c \tag{11}$$

Here $c(t, i_{k-N+1}, ..., i_{k-1}, i_k)$ denote the negative normalized log likelihood of track τ_t associated with measurement sequence $\mathbf{z}_{\mathbf{i}_{\mathbf{k-N+1}}}(k-N+1)$ up to $\mathbf{z}_{\mathbf{i}_0}(k)$ including all N measurement frames. There are several suboptimal methods of solving this integer program [12], [13], [14]. Linear program relaxation, [15] and Lagrange relaxation [13] and [14] are some methods. It is also possible to use several other cost functions in this formulation, such as distance between N frames of measurement target associations and normalized squared error.

Robotic mapping from known locations is equivalent to the above multiple target tracking problem. In this case it is also correct to assume that the measurement to target associations, are independent as there is no correlation between individual map elements. Therefore applying any target tracking methodology for the data association problem of robotic mapping is also possible. This independence assumption is strictly not true in SLAM as the measurements are correlated with each other. However, one approach to data association in SLAM is to assume measurement independence [7], [16]. This is mostly for reasons of clarity, simplicity, mathematical tractability and difficulty of obtaining the joint association likelihood. The independence assumption is also rationalized from the results obtained both in simulations and actual practice. Under these circumstances we can obtain the solution to multi-frame data association in SLAM by solving the integer programming problem (3) in the context of SLAM. Another approach is to implicitly address the measurement dependence by considering batch or group associations [8], [9] and [17]. It is this latter approach that is adopted in this work described.

III. DATA ASSOCIATION IN SLAM

A. Basic SLAM Framework

The basic framework [1], [2], [7] used in SLAM algorithms represents both the vehicle and the feature locations by absolute coordinates with reference to a global coordinate frame and is also used in this work. This formulation uses a composite map augmented state vector $\mathbf{X}$, consisting of concatenated 2D point landmark position vectors $\mathbf{m}_k$ (known as the map) and the vehicle pose $\mathbf{x_k}$ at time k.

$$\mathbf{X} = [\mathbf{x}_k^T \ \mathbf{m}_k^T]^T \tag{12}$$

Where $\mathbf{m}_k = [x_1^k \ y_1^k \ x_2^k \ y_2^k ... x_n^k \ y_n^k]^T$ and the vehicle pose is equal to $\mathbf{x}_k = [x_k \ y_k \ \theta_k]^T$. Here x_k, y_k and θ_k denote position coordinates and heading of the vehicle and $[x_i^k \ y_i^k]^T$, $i = 1,2...,n$ represent feature position vectors with respect to a global coordinate frame. In general, the motion model of the vehicle is nonlinear and can be represented in closed form as;

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k\text{-}1}, \mathbf{u}_{k\text{-}1}) + \mathbf{v}(k) \tag{13}$$

Where, $\mathbf{u}_{k\text{-}1}$ is the control input at time *k-1* and $\mathbf{v}(k) \sim N(\mathbf{0}, \mathbf{Q}_v(k))$. Assuming static landmarks, the process model of the map is expressed as follows:

$$\mathbf{m}_k = \mathbf{m}_{k\text{-}1} \tag{14}$$

The observation model is represented by

$$\mathbf{z}(k) = \mathbf{h}(\mathbf{x}_k, \mathbf{m}_k) + \mathbf{w}(k) \tag{15}$$

Where, $\mathbf{w}(k) \sim N(\mathbf{0}, \mathbf{R}(k))$. The composite state covariance (including map and the vehicle pose) matrix is denoted by $\mathbf{P}(k \mid k)$ and the observation prediction is specified by $\hat{\mathbf{z}}(k \mid k-1)$ then the EKF predictor equations are as follows:

$$\mathbf{X}(k \mid k-1) = \left[(\mathbf{f}(\mathbf{x}_{k\text{-}1}, \mathbf{u}_{k\text{-}1}))^T \quad \mathbf{m}_{k-1}^T \right]^T \tag{16}$$

$$\mathbf{P}(k \mid k-1) = \mathbf{F}\mathbf{P}(k-1 \mid k-1)\mathbf{F}^T + \mathbf{Q}(k) \tag{17}$$

$$\hat{\mathbf{z}}(k \mid k-1) = \mathbf{h}(\mathbf{x}_k, \mathbf{m}_k) \tag{18}$$

Where $\mathbf{F}$ is the Jacobian of the process model evaluated at time *k-1* and $\mathbf{Q}(k)$ is the composite process noise covariance matrix. When true observations ($\mathbf{z}(k)$) are available at time *k*, and after correct observation to feature associations are resolved using an appropriate data association algorithm, the EKF update is done as usual using the following equations.

$$\mathbf{e}(k) = \mathbf{z}(k) - \hat{\mathbf{z}}(k \mid k-1) \tag{19}$$

$$\mathbf{X}(k \mid k) = \mathbf{X}(k \mid k-1) + \mathbf{K}(k)\mathbf{e}(k) \tag{20}$$

$$\mathbf{P}(k \mid k) = \mathbf{P}(k \mid k-1) - \mathbf{K}(k)\mathbf{S}(k)\mathbf{K}^T(k) \tag{21}$$

Where, $\mathbf{e}(k)$, $\mathbf{S}(k)$ and $\mathbf{K}(k) = \mathbf{P}(k \mid k-1)\mathbf{H}^T\mathbf{S}^{-1}$ are the observation innovation, its covariance matrix and the Kalman gain with $\mathbf{H} = \partial\mathbf{h} / \partial\mathbf{X}(k \mid k\text{-}1)$. Landmark track initiation, maintenance and deletion are carried out here as in [7].

B. Multi-frame Data Association Framework

Because of the dependence between measurements, most suitable data association methods for SLAM are batch methods. However extending batch data association methods [8], [9] and [17] over multiple frames is NP hard. So to reduce the search space, we use a suboptimal method (in the sense we don't traverse the entire search space and instead select most probable hypotheses from a temporal consistency criterion). In this suboptimal method, measurement-target pairs consistent over a multiple frame window are selected as probable associations for SLAM. Then multiple frame measurement target associations over multiple frames are placed in an extended interpretation tree consisting of all possible measurement target combinations. If there are n_k measurements in the current frame, the interpretation tree consists of n_k levels. If, measurement i_k in $frame_k$ consists of f_k target-measurement combinations in the window of multiple frames, allowing for missed detections, spurious measurements and the map feature repetitions in the tree, we have a search space of $\prod_{k=1}^{n_k} f_k$ hypotheses. However, if the single return and single source constraints are imposed we have a reduced number of hypotheses. Traversing the hypothesis tree can now be done as in [9] or [8]. Here we use the method of [9] to determine the hypothesis with largest number of jointly consistent pairings as the most probable measurement –target association set.

The selection of consistent measurement target combinations is carried out using a distance measure. The advantage of this data association scheme employing multiple frames of measurements is that it resolves ambiguities due to temporal behavior of clutter and moving objects with good results, enabling also to reverse the previously taken data association decisions as in Multiple Hypothesis Tracking (MHT) filter in the tracking literature. This batch method can be further extended to the MHT form by considering all the measurement combinations without pruning at batch level and will inevitably causes a drain of computing resources in few iterations. This feature is not available with the known batch methods of data associations proposed for SLAM [8], [9] and [17] as they considered spatial correlation of measurements and targets only. Let $\mathbf{X}(k-N+1 \mid k-N)$ and $\mathbf{P}(k-N+1 \mid k-N)$ be the prediction of composite state vector and its covariance according to (16) and (17). In each subsequent prediction of the state vector and its covariance, we define the modified state vector and its covariance as in [18] by adding the current vehicle trajectory state to the last position of the state vector. As an example, predicted state vector and its covariance at time $k-N+2$ are as follows.

$$\mathbf{X}(k-N+2 \mid k-N+1) = \left[\mathbf{f}(\mathbf{x}_{k\text{-}N+1}, \mathbf{u}_{k\text{-}N+1}) \quad \mathbf{m}_{k\text{-}N+1} \quad \mathbf{x}_{k\text{-}N+1}\right]^T \tag{22}$$

$$\mathbf{P}(k-N+2 \mid k-N+1) = \begin{bmatrix} \mathbf{F}_v \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \mathbf{F}_v^T + \mathbf{Q}_v & \mathbf{F}_v \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{m}_{k\text{-}N+1}} & \mathbf{F}_v \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \\ \mathbf{P}_{\mathbf{m}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \mathbf{F}_v^T & \mathbf{P}_{\mathbf{m}_{k\text{-}N+1}\mathbf{m}_{k\text{-}N+1}} & \mathbf{P}_{\mathbf{m}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \\ \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \mathbf{F}_v^T & \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{m}_{k\text{-}N+1}} & \mathbf{P}_{\mathbf{x}_{k\text{-}N+1}\mathbf{x}_{k\text{-}N+1}} \end{bmatrix} \tag{23}$$

Where $\mathbf{F}_v$ is the Jacobian $\left(\partial \mathbf{f} / \partial \mathbf{x}_k\right)$ of the process model evaluated at time $k-N+1$ On subsequent predictions in the window of frames, this procedure is repeated augmenting the state vector from the appropriate trajectory states and predicting until the state vector and the covariance matrix at time k is obtained. Calculation of the measurement Jacobian H of the measurement model (15) now consists of three parts, Jacobian $\mathbf{H}_v$, corresponding to the vehicle states, Jacobian $\mathbf{H}_m$, corresponding to the map states and $\mathbf{H}_{traj}$ corresponding to the trajectory states added to the state vector.

$$\mathbf{H} = \left[\mathbf{H}_v \quad \mathbf{H}_m \quad \mathbf{H}_{traj}\right] \tag{24}$$

Let $\mathbf{H}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k)$ and $\mathbf{e}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k)$ denote the Jacobian and the measurement innovation representing a target τ_t associating with measurement sequence $\mathbf{z}_{\mathbf{i}_{k\text{-}N+1}}(k-N+1)$, $\mathbf{z}_{\mathbf{i}_{k\text{-}N+2}}(k-N+2), \ldots,$ $\mathbf{z}_{\mathbf{i}_{k\text{-}1}}(k-1)$, and $\mathbf{z}_{\mathbf{i}_k}(k)$ in N frames of measurement, $frame_{k-N+1}$, $frame_{k-N+2}$, $frame_{k-N+3}$, ……….. , $frame_{k-1}$, and $frame_k$ respectively is associated with the target τ_t. Then $\mathbf{H}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k)$ and $\mathbf{e}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k)$ are obtained by concatenating innovation sequences and appropriate Jacobians in the form of a composite innovation vector and a composite Jacobian matrix.

$$\mathbf{e}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k) = \left[(\mathbf{z}_{i_{k-N+1}} - \hat{\mathbf{z}}_{i_{k-N+1}})^T \quad (\mathbf{z}_{i_{k-N+2}} - \hat{\mathbf{z}}_{i_{k-N+2}})^T \quad \ldots\ldots \; (\mathbf{z}_{i_k} - \hat{\mathbf{z}}_{i_k})^T\right]^T \tag{25}$$

$$\mathbf{H}(t, i_{k-N+1}, i_{k-N+2}, ..., i_k) = \left[\mathbf{H}_{i_{k-N+1}}^T \;\; \mathbf{H}_{i_{k-N+2}}^T \; \ldots\ldots \; \mathbf{H}_{i_k}^T\right]^T \tag{26}$$

Here $\mathbf{z}_{i_{k-m}}$ and $\hat{\mathbf{z}}_{i_{k-m}}$ for all $m = N-1, N-2, ..., 1, 0$ consist of the true measurement of the feature t at time $k-m$ and its prediction at $k-m$. $\mathbf{H}_{i_{k-m}}$ is the Jacobian corresponding to the innovation vector ($\mathbf{z}_{i_{k-m}}$ -$\hat{\mathbf{z}}_{i_{k-m}}$). Omitting the index term, $(t, i_{k-N+1}, i_{k-N+2}, ..., i_k)$, the covariance $\mathbf{S}$ of the association is;

$$\mathbf{S} = \mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R}_{aug} \tag{27}$$

Here $\mathbf{R}_{aug}$ is the covariance measurement noise vector whose diagonal terms consist of $\mathbf{R}$. Then the Mahalanobis distance $D^2 = \mathbf{H}^T \mathbf{S}^{-1} \mathbf{H}$ is calculated and the association hypothesis is accepted only if the value of D^2 is less than the value of Chi-squared distribution of $\dim(e(t, i_{k-N+1}, i_{k-N+2}, ..., i_k))$ degrees of freedom at a confidence level. Once all the possible measurement target combinations in the multi-frame window for current measurements are selected, they are used to construct the interpretation tree. Traversing of the interpretation tree is done as in [9] and the hypothesis having the maximum number of consistent pairs is taken as the association hypothesis.

IV SIMULATIONS AND EXPERIMENTS

A scenario in which, an autonomous vehicle performing SLAM in a simulated environment using odometry and range bearing sensors is considered. The algorithms are tested for two frames of measurement in the multiple frame window and using the clutter model [10]. The data association is also tested with the standard nearest neighbour algorithm and batch association with JCBB scheme. The simulation environment consists of 100 point features and always at least 15 features are made visible. The clutter model used [10], consists of a clutter density of 0.001 returns per m^2 initially and it is varied as required by the testing. The number of clutter returns and their spatial locations in the environment are assumed to be Poisson distributed and uniformly distributed respectively. Vehicle odometry is considered to have an error of standard deviation 0.5 m/s in the speed sensor and an error of standard deviation 0.05 rad in the steering encoder. Fig 1 and Fig 2 show the results of SLAM with the Multiple Frame Temporal Consistency (MFTC). The well bounded localization errors in the simulations indicate the good performance of the MFTC algorithm. The data association using MFTC was also compared with standard nearest neighbour (SNN), and JCBB by performing several Monte-Carlo runs. The simulations show that MFTC is superior to the SNN and JCBB data association methods over a range of clutter densities as summarized in Table I. Effect of dynamic objects is modelled by objects traversing the simulated environment according to a Brownian motion model. This model assumes that the dynamic objects move according to velocities, which are constantly being perturbed randomly. The initialization speeds of dynamic objects are selected from a Gaussian probability distribution having a certain variance. The initialization coordinates of the dynamic objects are selected from a uniform distribution. The number of dynamic objects in an instance is obtained from a Poisson distribution having a certain density. This density is varied from 0.001 /m^2 to 0.01/ m^2. Table I shows the data association using MFTC under varying uniformly distributed clutter. In terms of track loss measure, it clearly outperforms JCBB and the SNN methods. Tables II and III show the track loss and rms error measures of MFTC, JCBB and NN methods for SLAM. Because of the temporal considerations, MFTC is clearly superior to JCBB and SNN as it filters out clutter due to dynamic objects as well.

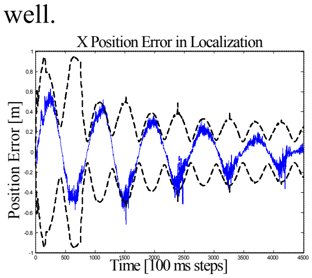

Figure 1- Error in X

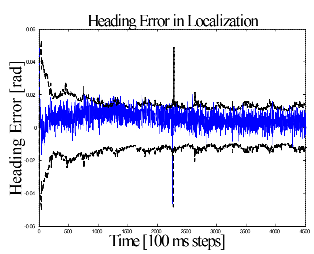

Figure 2 – Error in heading

Fig 1.and Fig 2-Localization error in full SLAM with the MFTC algorithm. Dashed line shows the three sigma bounds and thick line represents the localization error.

TABLE 1. COMPARISION OF ALGORITHMS

Data Association Algorithm	**Average % Track Loss per Feature** *False Alarm Density Per Unit Area*	
	0.001	***0.01***
SNN	2.7	15.1
JCBB	1.5	11.4
MFTC	1.1	8.8

TABLE II. PERFORMANCE WITH DYNAMIC OBJECTS

Data Association Algorithm	**Average % Track Loss per Feature** Dynamic Object Density Per Unit Area	
	0.001	***0.01***
SNN	3.2	18.4
JCBB	2.5	12.0
MFTC	1.4	8.9

TABLE III. ERROR PERFORMANCE WITH DYNAMIC OBJECTS

Data Association Algorithm	**RMS Error in Localization in X Direction** Dynamic Object Density Per Unit Area	
	0.001	***0.01***
SNN	0.4523	0.6820
JCBB	0.3522	0.4260
MFTC	0.2574	0.3251

Extensive experiments of the data association algorithm using multiple frame consistency criterion were carried out in an outdoor dynamic setting using Generic Outdoor Mobile Explorer (GenOME), a car like mobile robot. (Fig 3) The vehicle is equipped with SICK LMS 291 laser measurement system, GPS, gyroscopes and wheel encoders. Feature extraction for SLAM algorithms is carried out by simple clustering of the range bearing measurements obtained by the LMS. The points in a laser scan are clustered purely based on the distance among them. When the adjacent points are far apart by a specified distance, a new cluster is generated. Cluster centers were taken as features for SLAM algorithm. The estimated path and the feature locations of the SLAM experiment performed with batch 2 frame data association in a campus car park is shown in Fig. 4. The car park is a dynamic environment, with people, cars and bicycles moving around.

The well bounded innovations shown in Fig. 5 verify that the performance of SLAM is satisfactory with the data association algorithm. Figure 6, shows the estimated lateral and longitudinal uncertainty of the SLAM algorithm which indicate that estimated errors are reduced when more and more observations are used over the time to filter out the dynamic objects.

V CONCLUSIONS

A new multiple frame data association framework is proposed for robot navigation in the areas of robotic mapping from known locations and concurrent mapping and localization of mobile robots. The simulations and experiments show that the data association using batch temporal consistency criterion is superior to the standard nearest neighbour data association and JCBB in dynamic environments consisting of several moving objects such as people, cars and bicycles having varying speeds and sizes. The results also emphasise the importance of employing temporal correlations in the data association process where presence of dynamic objects and high density of spurious measurements hinders the data association performance.

Figure 3. Mobile robot used in SLAM experiments

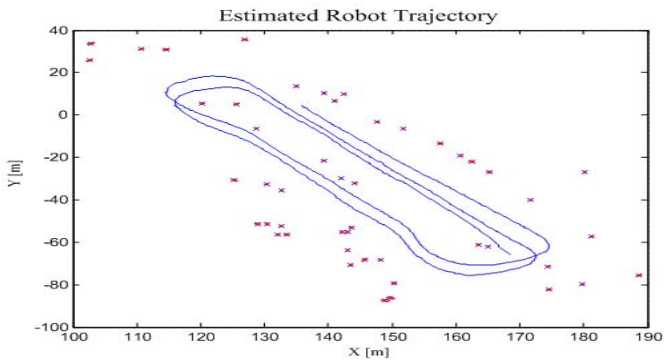

Figure 4. Estimated vehicle path (thick line) and feature locations(circles) (SLAM experiment in a campus car park).

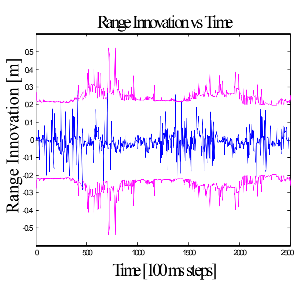

Fig 5 - Filter performance :Range innovation(dashed line) and its two sigma bounds(thick line).

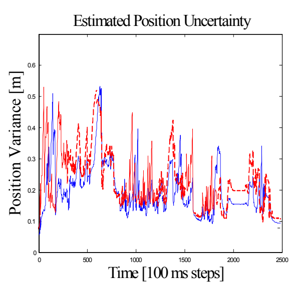

Figure 6. Variation of lateral (thick line) and longitudinal (dashed line) uncertainty

The future work under consideration includes integrating the new multi frame data association framework in all robot navigation tasks and studying of the complexity and means of efficiently traversing the search space of the interpretation tree.

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