Passive Multisensor Multitarget Feature-aided Unconstrained Tracking: A Geometric Perspective

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Abstract - Novel, targets-to-sensors' geometry-based performance measure, bootstrap estimation algorithm and feature-aided association are described for the passive multisensor multitarget data association, position and velocity measurement estimation and coupled unconstrained association/tracking problem. The approach reduces computational complexity and ghost targets, and provides dynamically changing geometry dependent on-line estimation of both the target's velocity measurements and the computation of the associated correlated position and velocity measurement noise covariance matrix (R-matrix). Sequences of these estimates, along with position measurement estimate sequences, serve as inputs to a Kalman filter tracker, associating/forming/de-ghosting and maintaining tracks in Cartesian coordinates. Based on state estimates of targets, a relative geometric measure-of-merit is used to select sensors for optimum tracking performance. Previous approaches to the passive multisensor-multitarget position state estimation problem did not incorporate feature-aided gating and association, and used R-matrix formulations, based on Cramer-Rao lower bound computations, which do not explicitly exploit the effects of the changing geometry. An overall system construct embodying the above features is described. The tracking performance efficacy of the new algorithmic system is demonstrated in a simulated self-organizing network of synchronized unattended acoustic Unattended Ground Sensors (UGS) using sequences of bearing measurement sets from triplets of UGS.

Keywords: Passive unconstrained feature-based tracking, geometric measure-of-merit, multivariate regression, estimation theory, sensor selection.

1 Introduction

1.1 Motivation

This paper considers the problem of unconstrained multitarget tracking using a self-organizing network of distributed passive acoustic Unattended Ground Sensors (UGS) [1]. The UGS are to detect, locate, track and identify targets of interest without the knowledge of road constraints [1, 3, 4].

In a previous group of related papers [1, 2, 3, 4] overall system constructs, algorithms and performance assessment were addressed. Problem specific topics covered included: (1) a geometric measure-of-merit, GMOM [5, 6] for optimum sensors-to-hypothesized-target geometry selection which minimizes the dilution of UGS bearing measurement errors into instantaneous target composite position measurement errors [5]; (2) a self-organization (SO) optimization (Genetic) algorithm for optimum selection of sensor groups to minimize the total network power utilization and the GMOM [6]; and (3) algorithms and performance assessment for multitarget localization, feature-based association, unconstrained vs. constrained tracking, target identification, and distributed track and identification (ID) declarations level fusion [2, 4, 7]. However, the implementation details of the algorithms were not addressed.

Therefore, as the main focus of this paper, a novel, targets-to-sensors geometry-based performance measure, bootstrap estimation algorithm and feature-aided gating and association are described. This is specifically for the passive multisensor multitarget data association, position and velocity measurement estimation and coupled association/tracking problem [8-13]. The approach reduces computational complexity and ghost targets, and provides dynamically changing geometry dependent on-line estimation of both the target’s velocity measurements and the computation of the associated correlated position and velocity measurement noise covariance matrix (R-matrix) of the Kalman filter tracker [1], and extends prior work [12, 13].

Previous approaches to the passive multisensor-multitarget position estimation problem used probabilistic weights rather than target features to prune association candidates, did not incorporate feature-aided gating and association, and used R-matrix formulations, based on Cramer-Rao lower bound computations, which do not explicitly exploit the effects of the changing geometry.
1.2 Scope and Organization of Paper

The paper is organized as follows. As part of review of prior work and to formulate the problem at hand, the significance and building blocks of unconstrained tracking in an UGS network is described. This in turn motivates the use of target (feature) identification (ID) information and ID fusion for reducing the number of ghost targets, and the subsequent use of ID in gating and feature-aided association.

The overall system construct is described delineating the elements of the tracking processing chain. The need for bootstrapping is discussed. Multivariate regression analysis is introduced as a means for estimating the velocity measurement vector for the Kalman filter. The need for dynamic R-matrix formulation is established. This ushers in need for error covariance analysis [6], and the use of multivariate regression formulation for the computation of the velocity measurement error covariance matrix.

Both recorded and simulated bearing measurements from a network of UGS are used to demonstrate, with and without the dynamic R-matrix formulation, under self-organization (simulated) sensor selection for optimum tracking performance.

2 Problem Formulation/Background

In the following sections the focus will be on qualitative, system level description of the kinematic aspects of the problem that is, how to optimally estimate the targets state and thereby generate continuous target tracks using a combination of measurements from selected ensembles of UGS.

Each UGS in the network provides time samples of bearing measurements with respect to a common reference. The location of the UGS are assumed to be also known to a common reference and all the measurements received at a central processing node (referred to as “gateway” [1, 3, 4]) are time synchronized. Measurements and data processing is assumed to take place at a common “gateway” processing node [1, 3]. Measurement propagation and communications delays between network nodes, UGS networking issues [1, 3] and distributed hierarchical fusion [7] of multiple gateways-based tracker outputs was previously considered [1, 3] and not addressed herein.

The geometry between the sensor and road is not required for unconstrained tracking. However, with multiple targets present in the sensors field-of-view, measurements from a triplet of UGS (at least two in a single target case) have to be associated before the target(s) positions can be estimated [1, 3]. A SO algorithm [2] is used to select the triplet of UGS in the network at a time, with respect to a geometric measure-of-merit (GMOM) [6] criterion, which minimizes the dilution of bearing measurement errors into instantaneous composite position measurement errors, based on the concept of the geometric dilution of precision, GDOP [5].

However, with three sensors and several potential targets in the sensor’s field-of-view (FOV), the intersections of the noisy bearing lines from the three sensors produce both “true” and “ghost” targets and false alarms [1, 3, 10]. This requires the ‘trilateration’ [14] instantaneous composite target position measurement estimation algorithm to be solved in combination with a 3-D association “de-ghosting” algorithm [1, 8-13] that reduces the number of false intersections (i.e., ghosts) which grow in a combinatorial fashion with the number targets [10]. Figure 1 illustrates a ghosting problem example with multiple targets present [3].

![Figure 1: Fictitious or “ghost” targets were generated in multi-target situations when using bearing angle measurements from three sensors. When different target types were present, checking the consistency of target ID data reported by the sensors significantly reduced the number of ghosts.](image)

When different target types are present (e.g., in a multiple target scenario), the number of ghosts can be reduced by using target ID data from each sensor. Those ghosts that do not have consistent ID data from two or more sensors can be eliminated. In this manner, triplets of bearing measurements from acoustic UGS and their associated target ID data can be processed by trilateration/de-ghosting [1, 8-13] and ID fusion/gating functions to generate true instantaneous composite measurement sets of estimated target locations in Cartesian coordinates. The target ID data declarations are associated with specific UGS bearing measurements and are fused using Dempster-Shafer theory [15].

Replicating the ‘trilateration/de-ghosting’ process for each sample time can then be used to generate time sequences of instantaneous target composite position measurement estimates. This process allows the generation of continuous target tracks and at the same time eliminates lingering “ghost” targets over time by an association and filtering (i.e., tracking) process. The time
sequence of instantaneous composite position measurement estimates become a component of the measurement vector of a linearized Kalman filter tracker in Cartesian coordinates with measurements equal to the states. Algorithms for the computation of the velocity measurement components and the dynamically changing measurement error covariance matrix elements for the Kalman filter are described in Section 4.

3 The overall system construct

The overall system functional architecture is depicted in Figure 1.

![Figure 1 Overall System Architecture](image)

Figure 1: Overall System Architecture

Synchronized time samples of selected multitarget-acoustic multisensor bearing measurements, associated bearing error variances, detection probabilities and target ID declarations are received at the central processing node (gateway). This data set will be referred to as centralized synchronized bearing measurement set (BMS). The BMS serve as input to position estimation (trilateration) and feature-aided association (de-ghosting) yielding partially de-ghosted targets and their position estimates in Cartesian coordinates [1, 3] This the new “instantaneous composite position measurement [13] set” will also be referred to interchangeably, as “partially de-ghosted position measurements”, (PDPM). The PDPM set contains the position estimates of both real and lingering ghost target, but it does not contain any associated position error covariance data.

In order to provide a continuous track of “real” targets and at the same time eliminate lingering ghosts, sequences of PDPM data sets are processed as the position measurement vector components in a six state, six measurements linearized Kalman filter tracker with a constant acceleration model [10] employing the Jonker-Volgenant-Castanon (JVC) assignment algorithm [16].

The tracker association algorithm uses a combined kinematic and ID feature based cost function (as well as ID gating and Dempster-Shafer ID declaration fusion) in order to reduce incorrect candidates for assignment. The ID feature-based cost function utilizes a “probabilistic” distance based on Dempster-Shafer “weight-of-conflict” [15, 17]. The states are equal to the measurements. It should be noted that six states are used to accommodate future passive sensors that provide both azimuth and elevation measurements. For this study only four states are utilized.

Since the PDPM set only contains position estimates, a separate “batch-position-sample-store” multivariate regression algorithm is used to estimate the velocity components of the targets. Since there is a delay of N-batch samples before the velocity measurements are computed, an initial constant upper bound estimate is used for the targets’ velocity measurements.

In addition of velocity measurement computation, the Kalman filter requires the computation of the measurement noise covariance matrix (R-matrix). Initially, an uncorrelated estimate is used for both the position and velocity components of the R-matrix.

3.1 Feature-aided association algorithm

The association algorithm [10, 12], associates, in this application, bearing (azimuth) measurements from S-lists (S = 3) to form “the instantaneous composite measurements” if the lists are all from the same time. A set of bearing measurements from a common sampling time constitutes a list. The three lists in this case consist of spatially distributed bearing measurements from three acoustic sensors taken at a common sampling time.

The association is constrained to be one-to-one (one measurement is associated with only one target). The problem is solved by minimizing the global cost of associating the each measurement with targets using an 3-D assignment algorithm [8-13]. The output of the algorithm is the number of targets present (some may be ghosts) and their estimated locations.

In order to reduce the number of ghost targets and at the same speed up computation time, target identification (ID) feature based declaration information from sensors is passed through the algorithm, as described previously. Multisensor ID gating and Dempster-Shafer [15] ID fusion used to prune the list and at the same time effectively augments the cost function to prune incorrect association candidates from the assignment thus significantly reducing computation time. Similar feature aided gating and association are used in the Kalman filter tracker [1, 3].

The cost function is a generalized likelihood function for target position in 2-D space with all the measurement assumed to be synchronized (i.e., same “time stamp”) to a common time reference. That is, a static association is solved for to obtain the “instantaneous composite measurements” [13]. The static association is solved for every new set of synchronized bearing measurement sequences. This is specifically the case when bearing only
measurements (which are incomplete position observations in the unconstrained case) are associated across sensors to find complete target position estimates while minimizing the ghost targets [10].

3.2 Bootstrapping

The position measurement error components of the R-matrix are obtained from a relative targets-to-sensors - geometry dependent error covariance transformation [5]. However, the error covariance transformation requires knowledge of the relative targets to sensor geometry. Initially, the targets states are not known so the relative geometry is not known. Therefore, once the targets’ state is estimated, it is fed back to the error covariance transformation algorithm. Therefore, at the next time step, the correct instantaneous composite position measurement error covariance matrix components are computed. With multiple targets present one can compute a new R-matrix for each target or use an average value if the relative geometry between the targets and the sensors is comparable, as determined by GMOM [6].

Having computed the instantaneous composite position measurements error components of the R-matrix, these components serve as inputs to the velocity measurement error computation algorithm. As described in Section 4 the position and velocity measurement errors are correlated. After these computations, the elements of the dynamically changing, geometry dependent elements of the R-matrix are continually updated with each time step.

4 Velocity Measurement Estimation

Regression theory [18] serves as the basis for velocity estimation using a batch of position estimate samples. The univariate model is introduced first, followed by the multivariate case.

4.1 The Univariate Regression Model

Consider, the model
\[ y(t) = \beta_0 + \beta_1 t + \epsilon, \]
where, \( \mathbb{E}[\epsilon] = 0, \epsilon \sim N(0, \sigma^2) \) (univariate Normal). While this is a generic model, in this specific case \( y(t) \) may represent y-position instantaneous composite measurement component over time, \( t \), and \( \epsilon \) is an additive zero mean noise term, representing the position measurement uncertainty.
\[ \mathbb{E}[y] = \beta_0 + \beta_1 t = \bar{y}, \]
called a regression line.

We want to find the regression coefficients (parameters), \( \beta_0 \) and \( \beta_1 \) of the model from observed position time series data. Here \( \beta_1 \) is the y-velocity component to be estimated.

Observed data is of the form, \( y_i = \beta_0 + \beta_1 t_i + \epsilon_i, i = 1, 2, \ldots, N \), where \( N \) is the time samples batch size.

In the linear regression model, we want to find \( \hat{\beta}_0 \) and \( \hat{\beta}_1 \) which minimizes
\[ S = \sum_{i=1}^{N} (y_i - \hat{\beta}_0 - \hat{\beta}_1 t_i)^2 \]
(3)

Differentiating \( S \) w.r.t. \( \beta_0 \) and \( \beta_1 \) and setting the resultant equations equal to zero, one obtains the “Normal Equations” [17], viz.,
\[ \beta_0 N + \hat{\beta}_1 \sum t_i = \sum y_i \quad \text{and} \quad \hat{\beta}_1 \sum t_i + \hat{\beta}_1 \sum t_i^2 = \sum t_i y_i \]

The solution of the Normal Equations yields
\[ \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{t} \]
(4)

where, the \( \hat{\beta}_1 \) is the y-velocity component estimate, viz.,
\[ \hat{\beta}_1 = \frac{\sum t_i y_i - \frac{1}{N} \sum t_i \sum y_i}{\sum t_i^2 - \frac{1}{N} (\sum t_i)^2} \]
(5)

and “bar” denotes “average operation”. The sample regression line is of the form:
\[ \eta = \bar{y} + \hat{\beta}_1 (t - \bar{t}) \]
(6)

The variance of \( \hat{\beta}_1 \) can be shown to be equal to:
\[ \text{var} \hat{\beta}_1 = \frac{\sigma^2 N}{\sum t_i^2 - \frac{1}{N} (\sum t_i)^2} \]
(7)

where, \( \sigma^2 \) is the y-position error variance and \( \bar{t} \) is the sample time increment.

4.2 The Multivariate Linear Regression Model

The general model is given by,
\[ y = \beta x + \epsilon, \]
(8)
where, \( y \) is a (1 x p) vector of “position” samples \( x \) is a (1 x q) vector of time sample increments \( \epsilon \sim N_p(0, \Sigma) \) is a p-variate Normal pdf \( \beta \) is a (p x q) matrix of “velocity” regression coefficients. The elements of \( \Sigma \) correspond to the instantaneous composite position measurement vector error covariance matrix, established in Section 4.4.
Given position estimates \( Y_{p \times N} = (y_1, ..., y_N) \) and time samples \( X_{q \times N} = (x_1, ..., x_N) \), the least squares estimate of \( \beta \) is given by:

\[
\hat{\beta} = Y' (X'X)^{-1}.
\]

4.4 Position Measurement Error Covariance Computation

The elements of the instantaneous composite position measurement error covariance matrix are a function of the sensors bearing error variances and the relative target-to-sensors geometry, which is shown in Figure 4. This figure depicts bearing lines from three sensors and one target in the x-y plane. Each sensor takes azimuth (bearing) measurement with respect to a common coordinate reference, say the x-axis in a Cartesian system. Typically, due to bearing measurement errors, the target is initially estimated in the bounding triangle shown in the Figure 4.

\[
\begin{align*}
\beta_x &= \left[ \sum x_i \sum x_i t_i \right] \left[ \frac{1}{d} \sum t_i^2 - \frac{1}{d} \sum t_i \right] \\
\beta_y &= \left[ \sum y_i \sum y_i t_i \right] \left[ \frac{1}{d} \sum t_i^2 - \frac{1}{d} \sum t_i \right] \\
\beta_z &= \left[ \sum z_i \sum z_i t_i \right] \left[ \frac{1}{d} \sum t_i^2 - \frac{1}{d} \sum t_i \right]
\end{align*}
\]

where \( d = N \sum t_i^2 - (\sum t_i)^2 \) and all sums are taken over \( i = 1 \) to \( N \).

4.4.1 Small Sample Asymptotic Normality of the Velocity Measurement Estimate

It can be shown [19, 20] that, due to the convolution of the probability density functions of \( N \) iid samples of the variables, small sample asymptotic normality is reached for \( N > 3 \). Therefore, the velocity measurement estimate is practically normally distributed after five batch samples.

4.5 Velocity Measurement Error Covariance Matrix Computation

The composite measurement velocity estimates were shown to be dependent on both the instantaneous composite measurement position estimate samples and sample time increments. It is a natural consequence that the composite measurement velocity error covariance matrix elements are a function of \( P_{2 \times 2} \).
From the multivariate model formulation, the velocity measurement error covariance matrix elements can be shown to be:

\[
\text{var} \left( \hat{\beta}_{ij} \right) = \sigma_{ij}^2, \quad \text{cov} \left( \hat{\beta}_{ij} \hat{\beta}_{kl} \right) = \sigma_{kl}^2 \alpha_{jk},
\]

where \( \left( \alpha_{ij} \right) = (XX')^{-1} \) and \( \left( \sigma_{ij} \right) = \Sigma = \text{covariance matrix of the p-variate additive noise term as defined above} \). The notation \( (\_\_\_\_\_) \) stands for “corresponding elements.”

In reference to the multivariate regression model, with \( p = 3 \), \( q = 2 \) and \( i = 1 \) to \( N \), the \( x \) and \( y \) composite velocity measurement component error variances and their respective covariance is given by:

\[
\sigma_i^2 = \left( p_{ii} \right)/d
\]

\[
\sigma_j^2 = \left( p_{jj} \right)/d
\]

\[
\text{cov}(x, y) = \left( p_{12} \right)/d
\]

where, \( p_{ij} \) are the elements of \( P_{2x2} \) (the position error covariance matrix) and \( d = N\sum t_i^2 - \left( \sum t_i \right)^2 \).

### 4.6 Elements of the Measurement Error Covariance Matrix

As a summary of the foregoing, in upper triangular form, \( R_k \) is given by (for six measurements),

\[
R_k = \begin{bmatrix}
\sigma_x^2 & \rho_x \sigma_x \sigma_y & 0 & 0 & 0 \\
\rho_x \sigma_x \sigma_y & \sigma_y^2 & 0 & 0 & 0 \\
0 & 0 & \sigma_z^2 \\
0 & 0 & 0 & \sigma_y^2 & \rho_y \sigma_y \sigma_z \\
0 & 0 & 0 & \rho_z \sigma_z \sigma_y & \sigma_z^2 \\
\end{bmatrix}
\]

Note that \( R_k \) consist of two upper triangular submatrices, one for position and one for velocity.

The “position” submatrix elements are obtained from a relative sensors-to-target geometry dependent error covariance analysis.

The “velocity” submatrix elements are obtained from the multivariate regression model. The “position” submatrix elements are input to the “velocity” submatrix elements computation. The “position” submatrix elements are a function of the sensor bearing error variances.

### 5 Performance Evaluation

The algorithms delineated in the system construct, described in Section 3, were implemented in a GUI-based simulation environment [1-3]. The simulation environment also contained the SO algorithm for optimum selection of acoustic UGS triplets.

#### 5.1 Geometry Induced Effects: Three Sensors

This data used herein consisted of recorded synchronized (time stamped) bearing measurement sets from a triplet of UGS [1, 3, 4].

Figures 5, 6 and 7 depict, in Cartesian coordinates, the geometrical sensitivity of the best estimate track and associated \( x \) and \( y \) tracking error variances respectively, with one triplet of sensors present throughout the entire target trajectory (within the detection range of the sensors). The tracker in this case utilized a dynamically changing \( R \)-matrix formulation. Figure 5 displays the sensor locations (circles), the ground truth (dotted line) and the best estimate target trajectory (BET) (dark line). It should be noted that the obvious upward bias error seen in Figure 5 between ground truth and the BET is caused by artificially introduced sensor bias errors and is not relevant to the current discussion.
The effects of geometrical sensitivities, predicted by GDOP [5], are shown by the sudden jump in the BET in Figure 5 and an increase of BET error variances., shown in Figures 6 and 7. These effects also occur at track initiation as expected, unrelated to GDOP. The GDOP caused jumps/error magnifications occur in the Figures just below the line connecting the top and bottom left sensor, and near the end of the track in the approximate direction of the line connecting the bottom and the right most sensor.

5.2 Geometry Induced Effects: UGS Network with SO

In contrast to the above result, simulation results shown in Figures 8 and 9 depict three closely spaced targets ground truth trajectories (dotted lines) in Cartesian coordinates. However, in this case there is only one target track present corresponding to the center ground truth trajectory.

The target track in Figure 8 corresponds to using an estimated R matrix, while Figure 9 is for the dynamic R-matrix case. In this simulation [1, 3] the entire surveillance area is randomly seeded with 115 acoustic UGS. The extent of the surveillance area is determined from known sensor detection ranges against anticipated targets. The SO algorithm [1, 2], using the GDOP (GMOM) criterion, knowledge of sensors detection range and FOV coverages (based on the knowledge of the estimated target(s) and sensor’s locations) selects groups of three sensors (triplets) at a given time step. SO using a Genetic Algorithm [2] selects, at each time step, optimal triplets of acoustic sensors that maximize the network’s tracking accuracy while minimizing its power utilization. As the track is generated, the SO algorithm monitors the magnitude of the GDOP [5] within a preset bound. If the bound is exceeded, SO using the best estimate and hypothesized (predicted) target locations computes the GDOP MOM [6] for a number of potential triplets of sensors within detection range and selects the triplet with the minimum error bound. As the target moves along new virtual trackers are started and the previous tracker data are handed over to the new tracker. The “previous” trackers are deleted. In some cases, multiple distributed track level data sets are fused together for reporting fused target states [1, 3]. In addition, some of the virtual trackers may share sensors from the selected triplet groups in order to minimize network power utilization [1-3]. In this fashion the sudden variations of target tracks caused by the effects of the geometrical magnification of the sensor bearing measurement errors into tracker input “composite measurement errors” are minimized. This effect was highlighted in Figure 5 for the three sensors case.

Tracks (BETs) with superimposed $\sigma_y^2$ error bars are shown in Figures 10 and 11 comparing the performance of trackers with an estimated R-matrix versus a dynamically changing R-matrix formulation in the presence of SO. We note the similarity in BET y error variance, $\sigma_y^2$, (with comparable results for $\sigma_x^2$ not shown for brevity) in both Figures as a result of optimum selection of sensors. We also note that using a dynamic R-matrix formulation results in realistic tracking performance unlike the estimated R-matrix formulation that yields an over optimistic performance.
6 Conclusions

New combination of algorithms consisting of a geometric measures-of-merit, covariance analyses, regression theory, and feature-aided gating and association were introduced for the passive multisensor multitarget unconstrained tracking problem. The new approach reduces false associations by reducing and subsequently eliminating ghost targets. The realistic tracking performance of the system was demonstrated with both recorded data and in a simulated SO network of UGS providing rules for optimum selection of sensors.

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8 References