Group State Estimation Algorithm Using Foliage Penetration GMTI Radar Detections*

Shozo Mori, Hui Hong
Systems & Technology Research
Woburn, MA USA
Shozo.Mori@STResearch.com

Pablo Arambel
Raytheon Company
Waltham, MA USA

Constantino Rago, Michael Shea, Patricia Davey
BAE Systems
Burlington, MA USA

Chee Chong, Steve Alter
Independent Technical Consultants

Abstract— **This paper describes an algorithm for integrating detections from Foliage Penetrating (FOPEN) Ground Moving Target Indicator (GMTI) radar, to recognize groups of dismounts moving through dense foliage, and to estimate the group states, including the group sizes and the directions of their movements. Difficulties of processing FOPEN GMTI radar detections are best characterized as low target-state-dependent detection probabilities and high non-uniform persistent false alarm densities. To overcome these difficulties, we use the Sum-of-Gaussian (SOG) Cardinalized Probability Hypothesis Density (CPHD) method to detect and track individual dismounts, and then, apply a group recognition method to the CPHD outputs to recognize the formation and the behavior of the dismounts groups.**

Keywords— Group tracking, SOG-CPHD tracking

I. INTRODUCTION

The Foliage Penetrating (FOPEN) Ground Moving Target Indicator (GMTI) radar is designed to detect moving objects through thick jungle-like canopies of foliage, based on the airborne UHF GMTI technology. As illustrated in Fig. 1, although the purpose of the system is to detect and track groups of dismounts, the radar will detect wild and domestic animals, vehicles, and any other objects with movements, including the water in rapids.
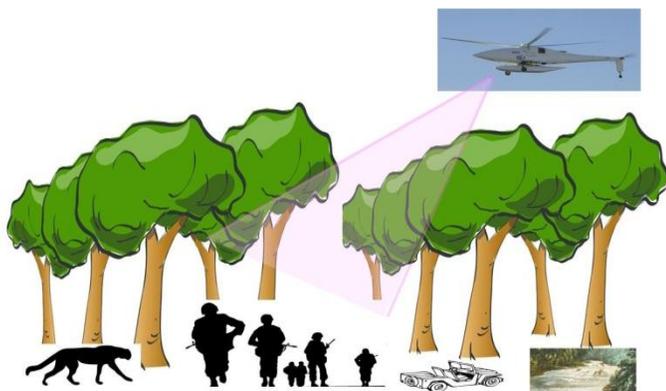

Fig. 1: FOPEN-GXP Concept

In short, the technical difficulties in using the FOPEN-GMTI radar can be summarized as (1) low detection probabilities and (2) high false alarm rates. It is very possible for a single object resulting in multiple detections, or for multiple objects ending up sporadic detections spatially and temporally. Like any other GMTI systems, the ground clutter is screened out by a properly designed Doppler filtering. However, we cannot avoid unwanted returns from moving objects of no interest, such as wind-blown leaves and branches, rapid and random river stream water flows, movement of animal inhabitants of various sizes, etc. Furthermore, in order to discriminate hostile elements from non-hostile elements including animal inhabitants, it is necessary to recognize the behaviors of the detected moving objects. To do so, we need first track individual objects, then recognize group formations (including singleton groups), and estimate their sizes and movements as accurately as possible.

Tracking groups of objects, or tracking multiple extended objects, requires not only tracking of individual members of groups or component observables of extended objects, but also hypothesizing group formations or observables for each extended object. Mathematically, such problems are best formulated using random finite sets or finite point processes, using Janossy measures as described in [14,15]. However, practical methods have been centered on using the so-called Probability Hypothesis Density (PHD) functions (or the first-order moment measures) [15,16,18-21], with several different approaches to relate the sets of groups with their members, or the extended objects with their component observables.

In this paper, we develop a rather simplified two-layer approach: On the lower layer, we track individual objects using the Cardinalized Probability Hypothesis Density (CPHD), like the GMTI tracking described in [13]. The uniqueness of our approach comes from a combination of the traditional track-oriented multiple hypothesis tracking (MHT) [7-9] with the seemingly tangential approach to tracking, i.e. the PHD tracking as described in [1-6,10-12].

Like the track-oriented MHT, our algorithm maintains the association hypotheses in terms of tracks, each of which is of constantly solving a combinatorial problem to obtain the best data association hypotheses for the track pruning purpose in the track-oriented MHT, we evaluate and maintain the

probabilistic weight attached to each track, as well as the associated posterior probability distribution on the number of targets. Each track is represented by a single Gaussian probability distribution on the target state space, and is updated with each frame of radar detections, together with the probabilistic weight assigned to each track (i.e., each Gaussian term in SOG).

The higher layer, called the group detection module, then extracts groups from the sum of the Gaussian terms that collectively represents PHD and individually represents tracks, i.e., hypothesized sets of detections originating from the same origins. This step will capture the group formation, the group movements, and the group merging and splitting. Essentially, this process will be performed on the outputs of the first layer on the frame-by-frame base, but we maintain the history so that the group behaviors are formed in time order. We call this two-layer algorithm group state estimation (GSE) algorithm. Fig. 2 shows the main processing modules that comprise the GSE.
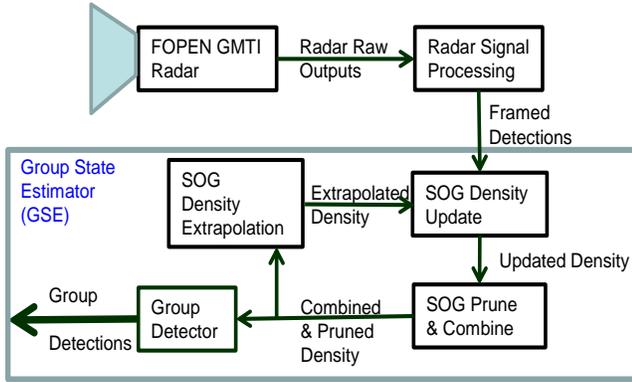

Fig. 2: Processing Flow of Group State Estimator (GSE)

The rest of the paper is organized as follows: Section 2 describes the sum-of-Gaussian target density estimation; Section 3 describes the group detection module; Section 4 explains some practical aspects of the GSE implementation; and Section 5 shows processing results under two quite different operating conditions. Conclusions are provided in Section 6.

II.   SUM-OF-GAUSSIAN TARGET DENSITY ESTIMATION

Let $y_1, y_2, y_3,...$ be the sequence of detection frames, each of which, y_k, is a sequence $y_k = (y_{k1},...,y_{km_k})$ of detections, with a random length (size) m_k, taken at the same time t_k, $k = 1,2,...$, as the output of the radar signal processing element. Each detection y_{kj} consists of a two- or three-dimensional positional measurement vector, a range rate measurement, and possibly, other individual detection information, such as the received radar cross section (RCS). As usual, we model each detection y_{kj} as a nonlinear projection $h_k(x_i(t_k))$ of the (true) state $x_i(t_k)$ of the target i (true origin), from which the detection y_{kj} originates, plus a measurement error modeled by an additive independent, zero-mean Gaussian random vector with a known (and announced)

covariance matrix R_{kj}, for the j-th detection in frame y_k, obtained at time t_k. The target state space E is a Euclidean space with an appropriate dimension, to represent the ground position and the velocity of each target.

We assume that the FOPEN-GMTI signal processor includes an appropriately effective clutter reduction function, including the (GMTI) ground clutter cancelation through the Doppler measurements.   However, each frame inevitably contains remnant false alarms, which are modeled by a Poisson point process with a given intensity measure density function γ_{FAk} defined on the measurement space for frame y_k. On the other hand, we model a rather complicated detection process by a seemingly simple mathematical formula: It is modeled, for each frame y_k, by a single function $P_{Dk} : E \rightarrow [0,1]$, where $P_{Dk}(x)$ is the probability of a target at state $x \in E$ being detected and included in frame y_k, such that $P_{Dk}(x)$ is the product of a constant $\bar{P}_D \in (0,1)$ with the probability ^{1} $\int_{FOV_k} g(y - h_k(x); R_k)dy$ of the potential measurement from a target at state x being included in the field of view, FOV_k (which includes Doppler window), of frame y_k, where R_k is the average measurement error covariance matrix.

The purpose of our GSE algorithm is to maintain the posterior target density function defined as the density function ^{2} $\hat{\gamma}_k(x)dx = E(\sum_{i=1}^{n} I(x_i(t_k); dx) \mid y^{(k)})$ for each $x \in E$, condition on the cumulative set $y^{(k)} = (y_1,...,y_k)$ of frames, so that its integral $\hat{\Gamma}_k(B) = \int_B \hat{\gamma}_k(x)dx$ over any measurable subset B of the target state space E is the expected number of targets whose states $x_i(t_k)$ are in the set B. The posterior target density function $\hat{\gamma}_k$ is expressed as the sum

$$\hat{\gamma}_k(x) = \hat{\gamma}_{Uk}(x) + \sum_{i=1}^{\hat{N}_k} \hat{v}_{ki} g(x - \hat{x}_{ki}; \hat{V}_{ki}) \qquad (1)$$

for every $x \in E$.

The density function $\hat{\gamma}_k$ contains the SOG term defined by a set $(\hat{v}_{ki}, \hat{x}_{ki}, \hat{V}_{ki})_{i=1}^{\hat{N}_k}$ of triples of the weights $\hat{v}_{ki}$, state estimates $\hat{x}_{ki}$, and estimation error covariance matrices $\hat{V}_{ki}$, each of which represents a weighted single Gaussian probability density function. The target density function of eqn. (1) also contains the density $\hat{\gamma}_{Uk}$ of the targets that have not been detected as detections at the k-th frame y_k, or in any other frames prior to frame y_k. In addition to the density

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[1] In this paper, g is the generic symbol for the zero-mean Gaussian density, i.e., $g(\eta; R) = \det(2\pi R)^{-1/2} \exp(-(1/2)(\eta^T R^{-1}\eta))$. By X^T we mean the transpose of a vector or matrix X.

[2] E is the symbol for conditional and unconditional mathematical expectation, and I is the generic indicator function, i.e., $I(\xi; A) = 1$ if $\xi \in A$, 0 otherwise.

function $\hat{\gamma}_k$, we maintain the posterior probability distribution represented by its probability mass $\hat{p}_k(n)$ for each assumed total number n of targets, conditioned by the cumulative set $y^{(k)}$ of frames up to y_k.

The GSE algorithm is similar to the so-called Cardinalized PHD (CPHD) algorithm, as described in [2,4,6], which is an extension of the PHD algorithm [1,3-5], the extension being obtained by removing a Poisson approximation. The most noticeable departure of the GSE from the standard PHD or CPHD filtering algorithms is the absence of targets' birth and death. Such exclusions are based on our understanding of the basic physics concerning targets and sensors. Namely, under normal conditions, in a relatively short period of time, no target is born or dies naturally. Moreover, any sensor cannot make any target born or killed, by means of changing the fields of view, or when targets get into or get out of the fields of view. Any target that is detected for the first time in a frame is not born between the previous two consecutive frames, but simply undetected in all the prior frames and detected in the current frame for the first time. Likewise, any target gets out of the field of view should not be considered as having been killed.

The exclusion of the target birth-death process is explained in more details in [6]. Nonetheless, the proper treatments of newly detected targets and targets leaving sensors' fields of view are very important under circumstances we are facing, i.e., very low detection probability and high clutter rate. In particular, the newly detected targets are properly treated by maintaining the undetected target density $\hat{\gamma}_{Uk}$ in (1), which is implemented as a multiple-dimensional step function. In the absence of the target birth and death, the extrapolation of the density function can be achieved by simply extrapolating each Gaussian term, in the exactly the same way as a standard Kalman or extended Kalman filter, with an appropriate target motion model, e.g., an almost constant-course-and-speed model, or the Ornstein-Uhlenbeck model. The extrapolation of the undetected target density can be achieved by an appropriate quantized target state transition model. Since the number of targets does not change in any extrapolation interval, the posterior probability $\hat{p}_{k-1}(n)$ does not have to be extrapolated.

Let the extrapolated target density for the k-th frame be $\bar{\gamma}_k(x) = \bar{\gamma}_{kU}(x) + \sum_{i=1}^{\bar{N}_k} \bar{v}_{ki} g(x - \bar{x}_{ki}; \bar{V}_{ki})$ for each $x \in E$, and the number-of-target probability mass function updated at the last frame be $\bar{p}_k(n) = \hat{p}_{k-1}(n)$, for $n = 0,1,2,...$ The GSE first calculates the track-to-detection (track-to-measurement) likelihood function defined by

$$L_{kij} = \begin{cases} \bar{P}_{Dk} \int_E g(y_{kj} - h_k(x); R_{kj}) g(x - \bar{x}_{ki}; \bar{V}_{ki}) dx & \text{if } i = 1,...,\bar{N}_k \text{ and } j = 1,...,m_k \\ \bar{P}_{Dk} \int_E g(y_{kj} - h_k(x); R_{kj}) \bar{\gamma}_{kU}(x) dx & \text{if } i = 0 \text{ and } j = 1,...,m_k \\ \int_E (1 - P_{kD}(x)) g(x - \bar{x}_{ki}; \bar{V}_{ki}) dx & \text{if } i = 1,...,\bar{N}_k \text{ and } j = 0 \end{cases}$$
(2)

These four kinds of track-to-detection likelihood functions correspond to (i) a target having been detected before and detected again in the current frame y_k, (ii) a target detected before but missed in the current frame y_k, and (iii) a target newly detected at the current frame y_k. The track-oriented MHT uses these likelihood functions to calculate track likelihood for each branched track by simple multiplication, and updates the target state estimates according to the track-to-detection assignments. The track likelihood for each track is then used to obtain the optimal data association hypothesis on a moving window of detection frames, when the track-oriented MHT is implemented in its standard form [7-9].

Instead of solving often time-consuming combinatric problems, the GSE updates the weight for each track as

$$\begin{cases} \hat{v}_{kij} = \bar{v}_{ki} L_{kij} W_{kj} \gamma_{Dkj}^{-1} & \text{for } i = 1,...,\bar{N}_{ki} \text{ and } j = 1,...,m_k \\ \hat{v}_{k0j} = L_{k0j} W_{kj} \gamma_{Dkj}^{-1} & \text{for } j = 1,...,m_k \\ \hat{v}_{ki0} = \bar{v}_{ki} L_{ki0} W_{k0} & \text{for } i = 1,...,\bar{N}_{ki} \end{cases}$$
(3)

using the double index[3] (i, j) for each track-detection pair, where $\gamma_{Dkj} \stackrel{\text{def}}{=} \sum_{i=0}^{\bar{N}_{ki}} \bar{v}_{ki} L_{kij}$, for each $j = 1,...,m_k$, is the predicted detection density at each detection y_{kj} in the measurement space. The weights, $W_{k0}, W_{k1},..., W_{km_k}$, and the updated the number-of-target (target-cardinality) probabilities $\hat{p}_k(n)$ can be calculated using the prior probabilities $\bar{p}_k(n)$ and the detection/false-alarm likelihood ratios defined as $r_{kj} = \gamma_{Dkj} / \gamma_{FAkj}$, γ_{FAkj} being the false alarm density at the detection y_{kj}, for $j = 1,...,m_k$, as shown in [2,4,6]. This calculation can be done at most with $O(m_k^3)$ because of the use of *elementary symmetric functions*, applying the i.i.d. (independent, identically distributed) point process approximation, as discussed in [2,4]. Finally, the density of undetected targets, represented by a multi-dimensional step function, is updated as $\hat{\gamma}_k(x) = W_{k0}(1 - P_{Dk}(x))\bar{\gamma}_k(x)$, and the double indices (i, j) are converted into the single indexing, to have eqn. (2) and complete the recursion.

In any track-oriented MHT algorithm, it is generally difficult to reduce the number of tracks through *combining operations*, without losing the integrity of the track tree structure, while the track pruning is usually depend on the generally time-consuming optimal data association on moving windows. The GSE algorithm, on the other hand, can use the track pruning and combining much more freely, as far as desired group separation and desired preservation of track histories are preserved.

III. TARGET GROUPING AND REPORTING

The estimation algorithm previously described lacks the ability to report "tracks" in the usual sense. That is, it does not report a set of track IDs that persist over time and reflect the evolution of individual targets. For the problem at hand, we

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[3] The double index (i, j) is used to represent each branched track generated by expanding the "old" track i by "new" measurement j. At the end of the update step, this double index will be converted to a single index in the form of eqn. (1).

are not interested in reporting individual tracks, but rather group tracks - or simply "groups." A group represents a set of targets (1 or more) that are close in terms of the individual kinematic states. In other words, a group represents individual targets that are near each other and moving in the same direction and at the same or almost the same speed.

In those cases where the probability of detection of an individual target is high and the targets are well resolved by the sensor, a possible approach to produce group tracks is to form tracks for individual targets using a standard report-to-track association approach, and then group the tracks. But when dealing with low probability of detection of individual tracks, it is very difficult to initiate and maintain tracks on each individual target. The approach used by the GSE is to extract group tracks directly from the set of Gaussian terms maintained by the state estimator, and propagate group track IDs as time evolves.

For these IDs to be meaningful, they need to reflect the evolution over time of the group track. There are four possible ways in which a group track can evolve between two consecutive observations: i) the group is a new group, ii) the group is a continuation of an existing group, iii) the group is a merge of two or more groups from the previous frame, and iv) the group is part of a split of a group from a previous frame. For each group in the current frame, the following logic is used to determine which one of the previous four possible cases is applicable:

i. <u>New group track:</u> If none of the terms in the current frame has a parent, a new group track ID is assigned to the group, and the group cardinality is set as the sum of the weights of the individual terms. This case occurs when all Gaussian terms in the group are new terms, i.e. each of them is generated by a detection that did not gated with any existing Gaussian terms on the previous frame.

ii. <u>Continuation group track:</u> If each term in the current frame has the same parent group track ID, the group track ID assigned to the group is the same ID of the parent group on the previous frame. The group cardinality is derived from the cardinality of the parent group updated with the estimated cardinality of the child group. This case occurs when every Gaussian term of the current group is derived from a previous frame Gaussian term (the parent) and all parent terms were grouped in the same group track.

iii. <u>Merged group track:</u> If the Gaussian terms of the current group were derived from previous Gaussian terms that belonged to two or more group tracks, a new group track ID is assigned, the lineage of the track is augmented with the two or more parent group track IDs, and the cardinality is reset to the cardinality of the new group. This case occurs when the groups have two or more different parents, or some are derived from an existing group while others do not have a parent.

iv. <u>Split group track:</u> If Gaussian terms from a single group separate, the group is split into two or more groups. In order to determine if a split has occurred, we first perform steps i-ii-iii to all groups. If two or more of the group track IDs in the current frame have the same group track ID, it means that both

are continuations of the same parent, i.e. the parent has split into two or more children. In this case, a new track ID is assigned to each group track, the lineage is augmented with the group track ID of the parent, and the cardinality is reset to the cardinality of each new group.

It is worth emphasizing that target grouping is only required for output purposes, and does not affect the group state estimation process described in previous sections. This is compatible with the system functional diagram depicted in Figure 2.

IV. PRACTICAL IMPLEMENTATION CONSIDERATIONS

After being generated as a newly-detected-target Gaussian term, each Gaussian term is recursively expanded in a tree expansion manner, in the exactly same way as in track-oriented MHT methods. For this reason, we can call each Gaussian term (and its associated history) a track or a track hypothesis. Without any gating, the number of tracks grows exponentially as at least $\prod_{\kappa=1}^{k} m_\kappa$ to the k-th frame, where m_κ is the number of detections in the κ-th detection frame. Gating reduces the number of track hypotheses generated in each frame, but still the total number of tracks can grow beyond the limit imposed by the processor capability to maintain real time performance. In order to maintain real time performance, we need to limit the number of tracks, and the goal is to do this without significant performance degradation.

In order to prevent this exponential explosion, we use two mechanisms to reduce the total number of tracks: (1) track pruning, and (2) track merging or combining, which are explained next.

Track Pruning: Track pruning is simply the elimination of *insignificant* tracks, which in turn tends to generate more insignificant tracks. We use a combination of the following hypothesis pruning methods:

1. *Threshold on Weights*: Eliminate a term $(\hat{v}_i, \hat{x}_i, \hat{V}_i)$ with $\hat{v}_i < \varepsilon_W$.

2. *Threshold on Misdetection Counts*: Eliminate a term $(\hat{v}_i, \hat{x}_i, \hat{V}_i)$ with the number of consecutive misdetections exceeds a given threshold.

3. *Out of FOV*: Eliminate a term $(\hat{v}_i, \hat{x}_i, \hat{V}_i)$ when its mean $\hat{x}_i$ goes out of the FOV.

4. *Uncertainty Size*: Eliminate a term $(\hat{v}_i, \hat{x}_i, \hat{V}_i)$ when $\det(\hat{V}_i)$ exceeds a given threshold.

When pruning tracks, however, we need to account for the reduction on the expected number of targets represented by the weights $\hat{v}_i$ of the Gaussian terms $(\hat{v}_i, \hat{x}_i, \hat{V}_i)$. Even if the individual weights $\hat{v}_i$ are small, the total expected number of targets being pruned can accumulate over time and bias the estimation. There are two approaches to prevent the total expected number of target to shrink, as explained next.

The first alternative is to think of the pruned targets as going back to the undetected state. Hence the number of pruned targets can be added to the undetected targets that may be "re-detected" in later frames, and distribute the eliminated total weight $\Delta\nu$ to each cell as $\Delta\nu_i = \dfrac{\mu_P(I_i)}{\sum_{i'=1}^{M}\mu_P(I_{i'})}\Delta\nu$ and inflate the density by $\Delta\gamma_{UDTPi} = \Delta\nu_i / \mu_P(I_i)$, for $i=1,...,M$ (i.e., by uniformly distributing the eliminated weight to each cell).

The second alternative for accounting the pruned weights is to adjust the weights of the surviving Gaussian terms so that the expected number of targets, before and after pruning, remains the same. This can be achieved by uniformly distributing the eliminated weigh among all surviving targets.

Track Merging: In some instances, a significant portion of the target mass is represented by a number of tracks (Gaussian terms) with similar weights. When that happens, pruning becomes ineffective because it either eliminates all the meaningful tracks altogether, or does not eliminate enough tracks. In this situation, the number of tracks can be reduced by merging tracks with similar state estimates.

In track merging, a set of tracks $(\hat{\nu}_i, \hat{x}_i, \hat{V}_i)_{i \in I}$ with an index set I that is a subset of the total index set $\{1,...,\hat{N}\}$ of all the Gaussian terms is combined into a single Gaussian term, $(\hat{\nu}_I, \hat{x}_I, \hat{V}_I)$, by interpreting the combined density function as a single-term Gaussian approximation of the sum-of-Gaussian distribution defined by the set of Gaussian terms, $(\hat{\nu}_i, \hat{x}_i, \hat{V}_i)_{i \in I}$. The single Gaussian term is computed as follows:

$$\begin{cases} \hat{\nu}_I = \sum_{i \in I} \hat{\nu}_i \\ \hat{x}_I = \left(\hat{\nu}_I\right)^{-1} \sum_{i \in I} \hat{\nu}_i \hat{x}_i \\ \hat{V}_I = \left(\hat{\nu}_I\right)^{-1} \sum_{i \in I} \hat{\nu}_i \left(\hat{V}_i + (\hat{x}_i - \hat{x}_I)(\hat{x}_i - \hat{x}_I)^T\right) \end{cases} \quad (4)$$

The set of tracks or Gaussian terms to be combined can be defined as an equivalence set determined by the equivalence relation induced by a combinability binary relation. A pair Gaussian terms, $(\hat{\nu}_i, \hat{x}_i, \hat{V}_i)$ and $(\hat{\nu}_j, \hat{x}_j, \hat{V}_j)$, can be defined as *combinable* if the so-called squared Mahalanobis distance $\chi_{ij} = (\hat{x}_i - \hat{x}_j)^T (\hat{V}_i + \hat{V}_j)^{-1}(\hat{x}_i - \hat{x}_j)$ is less than a given threshold $\bar{\chi}_M$, i.e., $\chi_{ij} \leq \bar{\chi}_M$. Alternative combinability is a proximity criterion determined by thresholding on $\|\hat{x}_i - \hat{x}_j\|$ and/or $\|\hat{V}_i - \hat{V}_j\|$.

The use of the Mahalanobis distance to determine combinability is computationally intensive but, as opposed to recursive merging approaches, it does not depend on initial conditions. The GSE mitigates this computational burden by first computing the Euclidean distance between all pairs, and then computing the Mahalanobis distance only among those pairs whose Euclidean distance is below a threshold.

V. PROCESSING EXAMPLES

The group state estimator was extensively tested using real data collected by the FOPEN Reconnaissance, Surveillance, Tracking and Engagement Radar (FORESTER) developed by SRC over multiple missions and locations, for scenarios with probability of detection as high as 0.8 (dismounts in open terrain) and as low as 0.3 (dismounts under double canopy), groups as small as 2 and as large as 8, moving slow or fast, and under varying conditions of wind-blown (tree movement) and stationary (water movement) clutter.
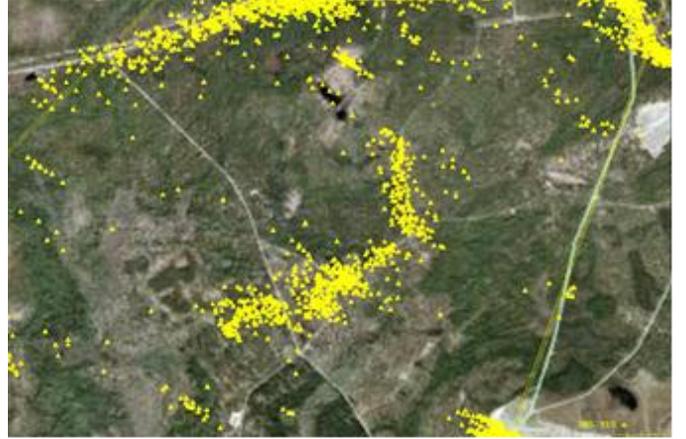

Fig 3: Raw GMTI (STANAG 4607) Data (Yellow Triangles) Collected on Ft. Stewart, GA (Multiple dwells are shown).

Fig. 3 shows an example of data collected under a single canopy area. The yellow triangles are detections generated by the front end signal processor over multiple dwells. The detections are due to a combination of true targets and false detections. Fig. 4 shows the ground truth and Fig. 5 shows the corresponding group state estimates. Except for one group, all other groups were detected and tracked, with position and cardinality estimates very close to the truth values, as shown in Fig. 5.

Fig. 4: Ground Truth for the Ft. Stewart Scenario in Fig. 3.

Fig. 5: Estimated group track position and cardinality obtained by data shown by Fig. 3. The ground truth is shown in Fig. 4.

A more challenging scenario corresponds to the data collected under a double canopy area shown in Fig. 6. In this case, the dismounts are moving under a double canopy forest, where again, as in the previous case, the yellow triangles corresponds to target detections and false alarms over multiple frames.

Fig. 6: Raw GMTI (STANAG 4607) Data (Yellow Triangles) collected under a double canopy forest (Multiple dwells are shown)

Still, the GSE was able to detect a group of dismounts milling around the center of the field of view, and provided a good estimate of the group size, as shown in Fig. 8. The corresponding ground truth is shown in Fig. 7.

Fig. 7: Ground truth for scenario in Fig 6.

Fig. 8: Estimated group track position obtained from the data shown in Fig. 6. The correct group size, 3, was obtained. There are a couple of false tracks.

VI. CONCLUSIONS

We have described a group tracking algorithm, which we call Group State Estimator (GSE), to recognize groups of dismounts moving through dense foliage, and to estimate the group states, including the group sizes and the directions of their movements. The GSE tracks individual target states as the target density function for the entire targets together, extracts group states, and maintains group track ID over time, accounting for group initiation, merge, and split.

The GSE algorithm is based on the sum-of-Gaussian, or Gaussian-mixture CPHD tracking approach, and is coupled with the group detection or recognition algorithm to identify the groups, estimate the size of each group, and the moving direction of each group, thereby providing information to infer the behavior of each group detection.

The GSE algorithm was tested using with a large amount of simulated data, as well as the data collected by FORESTER in several locations, under diverse foliage and weather conditions. A few examples were shown in the previous section.

REFERENCES

[1] R. P. S. Mahler, "A Theoretical Foundation for the Stein-Winter 'Probability Hypothesis Density (PHD)' Multiple Target Approach," Proc. MSS National Symposium on Sensor and Data Fusion, San Antonio, TX, June 2000.

[2] R. Mahler, "PHD Filters of Higher Order in Target Number," IEEE Transactions on Aerospace and Electronic Systems, Vol. 43, No. 4 October 2007.

[3] R. P. S. Mahler, "Multitarget Bayes Filtering via First-Order Multitarget Moments," IEEE Transactions on Aerospace and Electronic Systems, Vol. 39, No. 4 October 2003.

[4] R. P. S. Mahler, Statistical Multisource-Multitarget Information Fusion, Artech House, Boston, London, 2007.

[5] B.-N. Vo, and W.-K. Ma, "The Gaussian Mixture Probability Hypothesis Density Filter," IEEE Transactions on Signal Processing, Vol. 54, No. 11, November 2006.

[6] S. Mori, and C.-Y. Chong, "An Alternative Form of Cardinalized PHD Filter or I.I.D.-Approximation Filter," Proc. 10th International Conference on Information Fusion, Quebec City, Quebec, Canada, July 2007.

[7] S. Coraluppi, C. Carthel, M. Luettgen, and S. Lynch, "All-Source Track and Identity Fusion," in Proceedings of National Symposium on Sensor and Data Fusion, June 2000, San Antonio TX.

[8] S. Coraluppi, C. Carthel, S. Lynch, and D. Herrick, "All-Source Track and Identity Fusion: Recent Advances and Results," in Proceedings of National Symposium on Sensor and Data Fusion, June 2001, San Diego CA.

[9] S. S. Blackman, "Multiple Hypothesis Tracking for Multiple Target Tracking," AESS Systems Magazine, Vol. 19, Issue 1, Part2, 2004.

[11] M. C. Stein, "Recursive Bayesian Fusion for Force Estimation," Proc. National Symposium on Sensor Fusion, Vol. 1, Dallas, TX, March 1995.

[12] M. C. Stein, and C. L. Winter, "An Additive Theory of Probabilistic Accrual," Los Alamos National Laboratories Report, LA-UR-93-3336, 1993.

[13] M. Ulmke, O. Erdinc, and P. Willett, "GMTI Tracking via the Gaussian Mixture Cardinalized Probability Hypothesis Density Filter," IEEE Transactions on+ Aerospace and Electronic Systems, Vol. 46, No. 4, Oct. 2010.

[14] S. Mori, and C.-Y. Chong, "Multiple Target Tracking using Janossy Measure Density Functions," Proc. SPIE Symposium on Signal and Data Processing of Small Targets, San Diego, CA, August 2005.

[15] S. Mori, and C.Y.-Chong, "Tracking of Groups of Targets Using Generalized Janossy Measure Density Function," Proc. 9th International Conference on Information Fusion, Florence, Italy, 2006.

[16] D. Clark, and S. Godsill, "Group Target Tracking with the Gaussian Mixture Probability Hypothesis Density Filter," Proc. 3rd International Conference on Intelligent Sensors, Sensor Networks and Information, Melbourn, Australia, 2007.

[17] V. Edman, M. Andersson, K. Granström, and F. Gustafsson, "Pedestrian group tracking using GM-PHD filter," Proc. 21st European Signal Processing Conference, Marrakech, Morocco, 2013.

[18] K. Granstrom, C. Lundquist, and U. Orguner, "A Gaussian mixture PHD filter for extended target tracking," Proc. of International Conference on Information Fusion, Edinburgh, UK, July 2010.

[19] K. Granstrom, C Lundquist, and O. Orguner, "Extended Target Tracking using a Gaussian-Mixture PHD Filter," Transactions on Aerospace and Electronic Systems, Vol. 48, No. 4, October 2012.

[20] C. Lundquist, K. Granström and U. Orguner, "An Extended Target CPHD Filter and a Gamma Gaussian Inverse Wishart Implementation," vol. 7, no. 3, pp. 472-483, IEEE Journal of Selected Topics in Signal Processing (Special Issue on Multitarget Tracking), Jun. 2013.