Branching Ground Target Tracking using Sparse Manual Observations

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Abstract *– Work in the field of ground target surveillance of vehicles usually focus on elevated sensor platforms like unmanned aerial vehicles (UAV) or other aircraft equipped with advanced sensing systems. These systems yield high-resolution information, but with a limited coverage. In this work we focus on a different problem; when the data rate is very low (one detection per minute) and the sensors are ground stationed manual observers. High-resolution coverage is impossible to achieve in this scenario, and one must rely heavily on extra geographical information.*
The aim of this work has been to modify an existing product, the Saab Multi Sensor Tracker (MST), utilizing the Multi Hypothesis Tracking (MHT) association logic in the MST so that when the track reaches an intersection each branch in the MHT follows a different road segment. Additional branches have to be added to handle the problems of vehicles stopping or turning around at the intersections, and to handle off-road vehicles. The algorithm structure and design is detailed and simulation results using the modified MST are presented.

Keywords: Ground target tracking, manual observations, vehicles, road network.

1 Introduction

In many ways tracking of vehicles in terrain differs from established tracking applications dealing with airborne and maritime targets. For example roads, terrain and other types of surface constraints are much more rigid than in the established problems. On one hand these surface constraints can be used as an additional information source to improve the tracking performance. On the other hand the constraints can have a negative influence on the measurement data, e.g. the terrain causing cluttered and sparse target information.

Usually ground target tracking is focused on multiple vehicles in the terrain. Concerning the algorithm, when the number of targets becomes large the state space for the joint distribution over target states increases so much that it becomes practically impossible to maintain the joint distribution. One way to simplify the problem is by assuming that the targets move independently, and track each target using a separate filter, see e.g. [1]. Another way to deal with this is to propagate the first moment of the joint distribution, i.e. the probability hypothesis density (PHD) [2, 3].

Ground target tracking usually utilizes sensors on elevated platforms, e.g. unmanned aerial vehicles (UAV) and other aircraft. These sensor platforms often include advanced systems with high data rate capabilities, like Ground Moving Target Indication (GMTI), Synthetic Aperture Radar (SAR) and Forward Looking Infrared (FLIR). However, these airborne imagery sensor systems are expensive and their number will therefore be limited.

In this work we consider target reports from human observers on the ground. The manual observers have relatively low capacity, limited coverage, and may not give the same accuracy as imagery sensors. However, the false alarm rate from a manual observer is usually extremely low. The ability to distinguish target type, identity and affiliation is superior to automatic sensors. Another example is the capability of a human observer to use the terrain as a frame of reference (e.g. by using a Geographical Information System). However, information which is solely based on manual reports will hardly result in fire control tracking with a low target location error. In particular when the reports are sparse they are more suited for higher command level systems regarding, e.g., situation assessment and sensor management, or being a complement to systems with high data rate capabilities.

Further, the human observers equipment for creating reports has a relatively low cost and corresponding functionality is included in most of the different Soldier Modernization Programs (SMP) now ongoing all over the world. For example range can be estimated by using the firearms laser sight.

There are several research programs that have focused on manual reports as input data to generate a ground target situation awareness picture [3−7]. An interesting observation is that it seems fairly simple to establish a sensor network which is fed by manual reports. Given a communication network, it will always be possible for observers in the surveillance area (both civilian and military) to send reports and in that way being able to manage the demand of redundancy. As mentioned above, this kind of network will be possible at a much lower cost compared to advanced sensor platforms.

One of the contributions of this paper is that it applies an established tracking algorithm [18], originally developed for high data rates similar to the ones used in advanced airborne sensor platforms, to input data in the form of sparse manual reports. In other words, this paper shows the possibility to use the same type of tracking algorithm for both an airborne sensor platform and sparse sensor measurements in the terrain. This is of value since a ground situation picture will be calculated with input data from both types of sensors, see e.g. [24].

This paper is organized as follows. Sec. 2 relates this work to other achievements in the area. Sec. 3 details the architecture of the operational multi sensor tracker used as a basis for this work. The algorithm for ground target tracking using manual observations is described in Sec. 4, while Sec. 5 presents the scenario and test results used to evaluate the algorithm. The final section contains conclusive remarks and suggestions for future research.

2 Related work

Terrain tracking. The motion model for vehicles moving in terrain can be very unstructured, mainly because of the variation of terrain characteristics. In Kalman based methods like the Interacting Multiple Model (IMM) it is difficult to design a general model for the terrain effect [8, 9]. However, when using a simplified terrain description in 2D space, such as a map with only on/off road information, the IMM based algorithms are efficient [10]. Further, Variable Structure IMM (VS-IMM) including road information [23], especially road length and width [25], is successful.

There are several methods that are able to model the unstructured terrain features. The Hidden Markov Models (HMM) characterizes the target motion in an area with a rectangular grid, which describes target locations at discrete time instants, and transition probabilities between these states [10−11]. Another solution is to describe the influence of the terrain with a potential field [12−13]. A disadvantage with the potential field algorithm is its large computational cost [12]. And concerning the HMM, a comparison [10] with the IMM approach shows that the IMM is more efficient in a linearized scenario.

Finally, during the last decade the particle filter approach has been developed [14, 15, 26]. The method has been found efficient when solving tracking problems which include non-linear and non-Gaussian models of motion and measurements. Consequently the particle filter has been shown very interesting for ground target tracking scenarios, see e.g. [3, 9, 16].

Measurements. In our case the measurements are sparse manual observations, where ‘sparse’ corresponds to time intervals of the order of minutes. This has to be compared with the impression that ground target tracking articles often discuss scenarios where one has assumed that the time intervals, between sensor signals, are of the order of seconds. For example in [12] one compares the performance of different ground tracking techniques for different observation rates, and the time interval between sensor reports is varied between 3 and 15 seconds. In the scenario described in Sec. 5 a detection interval of 60 seconds is used. Further, the relevance of using larger time intervals can be illustrated by referring to [5] where one uses an army scenario, designed at the Swedish Defense Research Agency, which is generating intelligence reports about vehicles. In an average picture the time interval between consecutive reports is nearly one minute.

One cause for the manual observations to become sparse can be a low density of human observers in the surveillance area, and this can lead to an increased risk of delays in the target information transmission to a multi sensor tracker unit. This, combined with a natural variation of each human observers way of organizing his work process, can in its turn result in out-of-sequence measurements (OOSMs). During the last few years the OOSM tracking algorithms have caused quite a large interest, see e.g. [17]. For a tracking algorithm using sparse measurements it is of interest to be able to handle this problem.

3 The operational multi sensor tracker

Operational multi sensor trackers for air and surface surveillance are usually built to handle a few (around 5-20) sensors of vast coverage (several hundreds of kilometers). There are thousands of man-hours invested into operational systems, and in terms of reliability and performance it is very hard to achieve the same level of performance in new developments started from scratch. The idea in this work has been to benefit from the knowledge implemented in an operational system for air and surface tracking and tailor this system to work for ground target tracking as well. A prerequisite for this was a prior effort to include manual observer reports into the operational system, outlined in Sec. 3.2.

The operational system used as a starting point in this work was the SaabTech Multi Sensor Tracker (MST). The MST is a multithreaded C++ implementation of a real time data fusion engine. The MST should in this context be regarded as a generic operational tracking system and the aim of this work is not to describe the implementation into this specific system but in a more general manner describe how to alter an operational system to handle ground target tracking using sparse manual observations. In order to compare the system under consideration in this work with other operational systems, a brief description of the architecture of the MST is included in the following subsection.

3.1 Architecture

The MST is a real time multi target tracker for stand-alone or integrated operation that supports fusion of data from

- Primary and Secondary surveillance radar, with or without elevation
- Jam-Strobes
- Electronic Support Measures
- Electro-Optical sensors (IRST, Infra red search and track, FLIR/TV with video extractor)
- Positioning systems (GPS)
- Manual Observer Reports

Several different versions of this tracker exist. The one used in this work is implemented as a Microsoft Windows dynamically linked library, and is built around a kernel that employs the track oriented multiple hypotheses and Bayesian inference principles. This means that during the association of detections to tracks, the MST can evaluate a number of different hypotheses in each association step. This so called branching of tracks is based on a Bayesian score function, a probability density function (PDF) that determines the probabilities that the different associations are correct. The tracks/branches are updated with associated detections and employs a five state IMM filter. Each state is implemented as a Kalman filter or extended Kalman Filter (EKF) for the nonlinear states, see [21] for details regarding design of modern tracking systems.

The MST handles both plots (detections including range) and strobes (detections without range). The plots are handled by the following scheme, see Fig. 1.

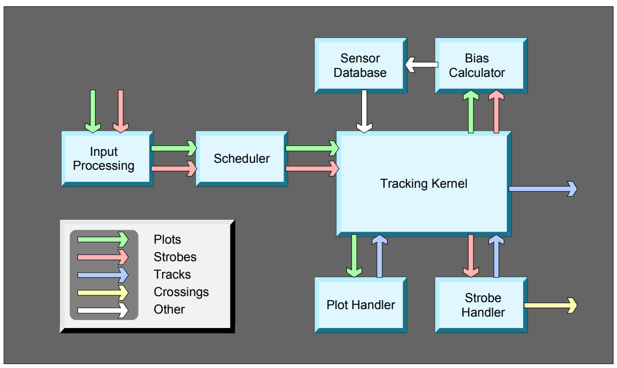

Fig. 1. Block diagram of the internal structure of the SaabTech sensor data processing module.

- When plots are received they are arranged in batches that are scheduled for processing in the tracking kernel.
- The tracking kernel compares each plot in a batch to each track that is currently managed by the kernel and is within the bounding sector of the plot batch. The result of these comparisons is the optimal association within the batch. The tracks are updated with their associated plots and the kernel outputs the result.
- Plots that cannot be associated with existing tracks are sent to the plot handler for automatic initiation of new tracks.
- The tracks and their associated plots are sent to the bias calculator that, based on the difference in the plots from one sensor to another, computes near constant sensor errors in for example position, time and axis alignment. The bias calculator runs separately and only when the load allows for it. More information regarding the bias calculator can be found in [20].

Reference and background information on the SaabTech MST and the principles behind it are found in [18] and [19].

3.2 Manual observations for air and sea

Support for manual observer reports for air and sea surveillance was recently integrated into the MST during a customer evaluation effort [22]. These manual observers have several peculiar features that makes them suitable to model observers watching for ground targets as well. The observer reports used for air and surface surveillance come in two different types

- Type 1: 2D plot type where the range and azimuth is divided into fairly large intervals. The observations has a maximum range of 25 km, a limit which corresponds to an air target observed with binoculars. Range was reported using three intervals [0..3 km], [3..8 km] and [8..25 km]. The azimuth has a resolution of $\pi/4$.
- Type 2: 2D strobe type where azimuth and elevation is reported by using a laser pointer.

The target reports from the manual observers are rather unlike the kind of data obtained from conventional sensors such as radar, ESM and IRST. The Type 1 observations are non-Gaussian, all manual observations have a tendency to give high and varying latency and each observer have very limited capacity to update several targets at a time. More details regarding the integration of manual observers in the MST is given in [22].

4 Method

The modification of the operational multi sensor tracker consists of

- Support for road network constrained movement.
- Utilize the multi hypothesis logic for prediction of multiple parallel vehicle positions along the road segements.
- Observer reports of only one type, Type 1. The possible range and azimuth values are adapted to the ground target scenario, see Table 1.

4.1 The road network

The freedom of movement of a ground target is very much affected by the geographical conditions of its surroundings. For example, a car cannot cross a lake or a swamp without a bridge. If passage is possible it is at least hampered by rough terrain, which therefore often is avoided. For instance, an off-road route might be shorter but considerably slower than a route along paved roads.

The supposition here is that the vehicles stay on roads in most cases, and that this has to be taken into account when associating detections to tracks and when updating tracks. To accomplish this the possibility of having a vector road network such as the one in Fig. 2 has been added to the operational target tracker. It consists of a number of road segments that are connected to each other at junctions. Each road segment is a straight line with no specific width, but a width could easily be added later and also given meaning as the width of the road to control the uncertainties of a tracks location perpendicularly to the direction of the road. Further, this paper does not discuss the accuracy of the road information which is assumed to be ideal.

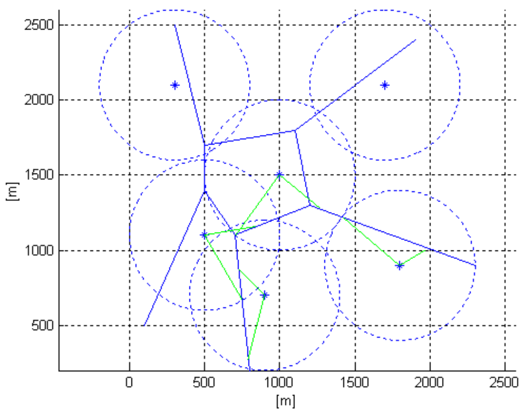

Fig. 2. The artificial road network used in the validation (solid lines), fixed observer positions (stars) and their maximum range (dotted lines), example measurement set (thin lines).

4.2 The multi hypothesis principle

The IMM models in the operational tracker are designed for air targets and include models such as coasting, slow turns etc. This is not suitable for ground target tracking, since these targets move in different patterns than air targets. With sparse observations the target may pass one or several junctions between each measurement update. This demands that the ground target tracker consider several partly independent alternatives during the prediction of each track. The solution to this problem could be to develop new filters such as particle filters or VS-IMM filters [23] in which each road section is represented by a mode in the IMM structure. In this work, the idea was to see if one could retain the IMM filters and alter the MHT implementation instead.

MHT is normally a way to take several detection to track associations into account by forming branches of each track. Thereby deferring the choice of the correct association until later. In order to improve ground target tracking we changed the MHT in such a way that when a track is propagated to a road junction it is split into a number of branches, each following one of the roads leaving the junction. When a track approaches a junction the following algorithm is used.

Algorithm 1 Branch Split

1. Stop the main branch at the junction.
2. For each new road
    a. Make a copy of the current branch.
    b. Rotate the velocity vector of the new branch to the direction of the new road.

There is an example of road branching in Fig. 3. The two smaller symbols with velocity vectors heading almost straight to the west and to the south are branches created by the branching algorithm.

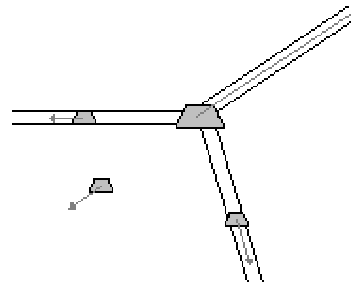

Fig. 3. A track and its branches at a junction

In Fig. 3 there is one branch that is heading approximately southwest. This is the off-road branch. It always exists to pick up detections the deviates from a road, for example if the target leaves the road. At the junction in Fig. 3 there is a large symbol without a velocity vector. This is the main branch and it has been stopped at the junction to take care of the case where the target stops or turns around at the junction. After receiving an observation that is associated with one of the branches of the track, that branch becomes the main branch and all others are removed. At the next propagation step, a new off-road branch is created. The situation after the next association is shown in Fig. 4 where the new off-road branch is situated *inside* the main branch.

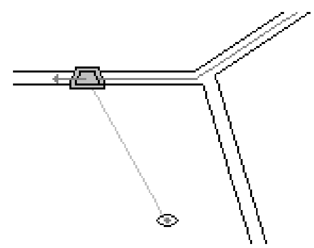

Fig. 4. The same track as before, after the update

The off-road branch is handled separately from the other branches. All branches except the off-road branch are closely tied to a single road, whereas the off-road branch is totally unconnected. The other branches are forced to stay on the road and move in its direction, but the off-road branch is free to move away from all roads.

Since we regard the chance for false observations to be very low, we can derive a lot of confidence that there actually is a target at the specified location from a single observation. Therefore we initiate new tracks based on one single detection only, if that detection has not been associated to a track. The speed is initialized to the true speed used in the validation (10 m/s) but with a large covariance.

5 Validation

In order to validate the developed ground target tracking functionality, a quantitative existence test was needed. In other words, since the quality of the tracks is low and fairly unimportant, we chose to evaluate the tracking solely on the basis of the percentage of tracks that follow the paths of their true targets.

5.1 The manual observations

The manual observers were used as a basis for defining observations for ground targets. The focus of this work is on the aspects of data fusion using very sparse information. In our simulations we allow for the observers to report detections once every 60 seconds. But on the other hand, there are no false detections. This implies that when the observers report a target, one can place a very high confidence in that information. These facts ensure that great confidence can be put in created tracks, but also that targets can be missed easily.

We assume that targets travel predominantly by road, and that most alterations of target heading and speed will occur at the intersections. The observable area is defined by the line of sight. In these evaluations the maximum reported range has been limited to 500 m. The target report consists of range, azimuth, time of detection, road segment, and direction of travel. Table 1 shows the simulated accuracy for the observers.

Table 1 Detection data information

	Step	Max	σ
Range	50	500 m	25 m
Azimuth	NA	$2^*\pi$	$\pi/16$

The manual observers for ground targets are able to measure a continuous range of azimuth but a discrete set of range values using, e.g., a firearms laser sight.

5.2 Scenario

The simulation setup from Fig. 2 was used in the validation. In the road network of Fig. 2 there are five entry points and exit points beyond which we suppose that nothing is visible. We also suppose that all the road segments of the network are wide enough for two vehicles to pass and meet each other. There are five stationary observers, indicated by stars in the figure.

The simulation validation was performed using one to five different of vehicles on the network simultaneously. Each validation consisted of 20 independent Monte Carlo runs of five minutes duration each using vehicles moving randomly through the road network of Fig. 2. For each run, the entry point was chosen randomly for each vehicle. They entered at random times that were relatively close to each other. The vehicles traveled to their destinations at 36 km/h. Their destinations were also chosen randomly as one of the exit points that did not coincide with their entry points. The scenario includes several cases when two vehicles meet and pass each other and move side-by-side.

5.3 Results

All tests were successful and showed that the concepts developed are able to track the simulated vehicles in the defined scenario. Even with five simultaneously tracked vehicles the MST managed to sustain tracking on each target when crossing or passing each other on the road network. The positional root mean square error was less than 60 meters.

The reason for the successful validation even in cases with very dense traffic is that we have no false measurements, measurement to hypothesis association is clear since the measurements include a road number, the measurement noise level is quite low and the targets do not start/stop or change speed.

6 Conclusions

We have modified an operational real-time multi sensor tracker for air and sea surveillance, where the input data is characterized by high rates, into a ground target tracker that is using sparse manual observations as input data. The system is based on multi hypothesis tracking (MHT), and in our case we have focused on the road network as the origin for the generation of hypotheses. The contribution of this paper has been to show that it seems manageable to apply this type of tracking algorithm to both high input data rates, similar to the ones on an airborne sensor platforms, and sparse sensor measurements in the terrain. This is of interests since a ground situation picture preferably will be calculated with input data from both of these sensor types, see e.g. [24].

The numerical results for simplified simulation scenarios showed that the real-time multi hypothesis ground target tracker managed to track the vehicles that travel on the road network.

6.1 Future work

There are several ways to continue this research. Firstly, one needs to improve the simulation scenario so that it will include target reports about off-road vehicle motion. This will call for a development of the process that generates hypotheses, especially the off-road ones. The starting point for such a development will be an analysis which combines geographical information systems (GIS) data with analytical models which capture the capabilities of specific vehicles to move with a certain speed in a given area, see e.g. [13] and references therein.

Secondly, a ground situation picture is complex and contains a large number of targets. Since we use an operational real-time multi sensor tracker which is originally adapted to a large number of air and sea surveillance targets, it is of interest to investigate the ground target trackers capacity concerning number of targets.

Finally, by including other types of information one can compensate for the manual observations being sparse and in that way improve the management of hypotheses. E.g. absence of reports, ‘negative information’, can be used if one knows the surveillance view of the human observer. Another interesting aspect is to investigate the ramifications of out-of-sequence measurements (OOSMs).

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