Multiple Target Tracking with Navigation Uncertainty

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The goal of concurrent mapping and localization (CML) is for a mobile robot to build a map of an unknown environment while simultaneously using that map to navigate. CML can be considered as a problem of multiple target tracking (MTT) in the presence of navigation uncertainty. Although data association errors can have a catastrophic effect on CML performance, previous approaches to CML, such as stochastic mapping (SM), have either ignored the data association problem, matched features by hand, or used a nearest-neighbor approach [4, 2]. We have developed Integrated Mapping and Navigation (IMAN), a multiple hypothesis approach to CML that generalizes SM to incorporate data association uncertainty and expands multiple hypothesis tracking (MHT) to accommodate navigation error. This paper summarizes IMAN and illustrates its performance for a simulation of an autonomous underwater vehicle (AUV) navigating with forward-looking sonar.

SM uses a monolithic state vector and error covariance matrix. In IMAN, the vehicle model and each proposed feature are represented by a distinct model. This model separation is introduced to provide increased flexibility in modeling as well as to account for the multiple simultaneous estimates which are allowed within a multiple hypothesis framework. At any given time step, IMAN produces a *set* of state estimates and estimate error covariances for the vehicle and each feature. These estimates represent the possibilities depending on which of the proposed hypotheses are ultimately accepted as valid.

Although the combination of a multiple-hypothesis approach and vehicle navigational uncertainty prevents the clustering or partitioning common to multiple target tracking, state estimate separability is maximized using decision dependency sets. In this way, orthogonal decisions do not result in increased track tree size. A new technique for assignment formation and likelihood calculation integrates target-to-track and data-to-data associations. New track updating procedures account for the inseparability of target-to-track and data-to-data associations. Modified pruning strategies reduce algorithmic complexity and ensure track tree consistency.

Figure 1 summarizes the IMAN algorithm, which consists of the following steps [3]:

1. **state projection**: possible vehicle and feature states from the previous cycle are projected using the individual vehicle and feature models;
2. **match hypothesis formation**: measurements are compared to existing feature models to determine possible data association matches;
3. **additional hypothesis formation**: additional hypotheses concerning measurement source, existing feature disposition, and new feature identification are formed in cases where data association is ambiguous;
4. **feature track updating**: feature track trees are updated to reflect the feature disposition hypotheses which have been formed;
5. **vehicle track updating**: the vehicle track tree is updated to reflect the possible navigational events for the current cycle; and
6. **pruning**: the vehicle and feature track trees are pruned to remove estimates reflecting unlikely events and to enforce consistency.

A hypothesis is the association of a feature track and a measurement, asserting that a given measurement arises from a specific proposed feature. The goal of data association resolution in IMAN (steps 2 and 3) is to recognize ambiguous situations and to adapt to them as they occur. Match hypotheses are formed by comparing measurements with a predicted measurement based on combinations of possible projected vehicle states and compatible possible projected feature states for existing feature tracks. While each feature is restricted to one of a set of hypotheses about its disposition, the vehicle takes part in all of the measurements in a given time step. Because of this, vehicle track updating cannot take place on the basis of individual hypotheses, but rather must be based on sets of hypotheses spanning the decision space of the tracks and measurements for that time step. An assignment is an exhaustive, consistent set of hypotheses spanning this decision space. Each assignment will explain the disposition of each proposed feature and the origin of each measurement in a consistent manner. The first step in updating the vehicle track tree is the formation of all such possible assignments from the feature gating and measurement origin decisions. All assignments must be considered because (1) target-to-track associations are not equi-probable for IMAN and (2) the assignment likelihood calculation process requires consideration of all possible assignments.

During vehicle update tree growth, state likelihood is calculated conditioned on the decision to accept the root likelihood, but not on the truth of that likelihood. Forming the assignment root state results in some base likelihood derived from the number of features detected and missed and the number of measurements which are false alarms and real targets. Match hypothesis updates are multiplied by their gating probability (as in feature track updating). The leaves of the vehicle track then form an exhaustive, mutually exclusive set of possible events. The *a posteriori* probability of each assignment is then the normalized sum of the leaf states to which it gives rise. The second stage of vehicle track update tree likelihood calculation begins by setting the assignment root state likelihoods to the product of the parent state likelihood and the *a posteriori* assignment likelihood. The update portion of the tree is then renormalized so that the leaves of any branch sum to the probability of the root state for that branch.

The IMAN algorithm has been completely implemented in C++. A representative simulation run is shown in Figure 2. Improved track initiation techniques increase the range of situations in which the algorithm can operate, however complexity faults are encountered in situations with significant target interaction [3]. Improved hypothesis generation and pruning strategies are in development to prevent such situations where extreme growth of track tree size is encountered.

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References

[1] I. J. Cox and J. J. Leonard. Modeling a dynamic environment using a Bayesian multiple hypothesis approach. *Artificial Intelligence*, 66(2):311–344, April 1994.

[2] P. Moutarlier and R. Chatila. Stochastic multisensory data fusion for mobile robot location and environment modeling. In *5th Int. Symposium on Robotics Research*, Tokyo, 1989.

[3] C. M. Smith. *Integrating Mapping and Navigation.* PhD thesis, MIT, 1998.

[4] R. Smith, M. Self, and P. Cheeseman. Estimating uncertain spatial relationships in robotics. In I. Cox and G. Wilfong, editors, *Autonomous Robot Vehicles*. Springer-Verlag, 1990.

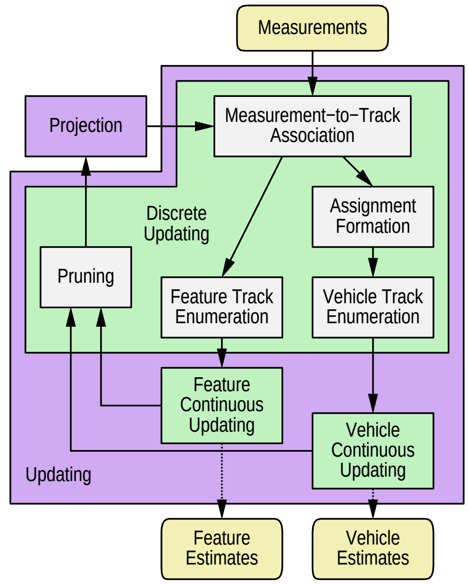

Figure 1: Process flow in IMAN.

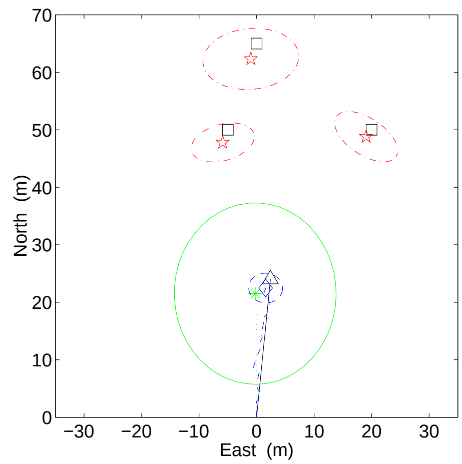

Figure 2: Representative IMAN simulation run. Three point-like targets are used to improve the navigation estimate. Actual target locations are displayed as squares. The vehicle is attempting to travel directly north in the presence of an unknown cross-current. The actual vehicle path is shown as a solid line, with its final position indicated by a triangle. Uncertain relative measurements of the features are received each second. The dead-reckoned vehicle path is shown as a dotted line, and is its three-sigma error ellipse is a solid line. The final dead-reckoned estimate of vehicle position is indicated by an asterisk. Using IMAN, vehicle navigation performance is improved and the features are mapped. The IMAN estimated vehicle path is shown by a dashed line, the final position estimate by a diamond, and the final three-sigma error ellipse by a dashed line. The final feature estimates are displayed as stars with their associated three-sigma error ellipses indicated by dashed-dotted lines. Feature measurements are degraded by non-unity probability of detection and the presence of clutter. IMAN successfully maps and models the features while rejecting spurious measurements and recovers vehicle motion in the presence of an unknown cross-current. Position uncertainty is greatly reduced by the incorporation of environmental data, using the three targets as positional references.