Neural Network Sensor Data Fusion Methods for Naval Air Traffic Control*

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Abstract: Sensor data fusion, involving data from multiple types of radars and other sensors is an aspect of improving naval air traffic control systems for aircraft carriers and amphibious ships [Pap et al., 1990]. The neural network technology can be applied to perform shipboard multisensor fusion of similar and dissimilar data for high confidence target identification.

The neural network concept is designed to fuse data from a variety of input sources such as Radars, IFF systems, Electronic Warfare Systems, Communication & Navigation Systems (e.g. JTIDS), and Command and Control Systems (e.g. NTDS). The system will fuse similar source data, (i.e. position)/velocity/acceleration), and dissimilar source data (i.e. frequency/prf/prt, etc.) to make a declaration of the identification of the source of the data.

A cooperative-competitive neural network is being used as a key component in a data association and fusion system for the tracking of interacting targets in a simulated noisy environment. Its architecture is well suited to recognizing relationships in images or data. Measures of the target kinematics were used in the neural network for data association. However since the cooperative-competitive neural network is a computationally complex algorithm, this neural network is reserved for situations when other techniques were unable to resolve the matching conflicts between target tracks and target detections. The output of this neural network is then combined with other sensor derived positions to create a refined estimate of each target track in the sensor fusion process.

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1.0 Introduction

The multi-sensor data fusion system using neural networks has been applied to these three major components; data association, data fusion, and target classification / identification. The sensor fusion challenges are defined in Waltz & Llinas [1990 and references contained therein]. They comprise two sets of task constraints. First, incoming target data from multiple sensors (possibly located in different positions and accessing data at different rates) must be correlated with existing master target tracks. In some cases, new master target tracks must be initiated. Tracks which have been inactive for a period of time and false alarms should be deleted from the active set of master target tracks.

The use of neural networks for sensor data association introduce an innovative approach to finding the best match between new targets and existing target tracks. This approach, using a multilayer cooperative-competitive neural network, provides a robust means for identifying the best one-to-one matches out of a set of possible many-to-many matches. It accomplishes this using a neural network which operates on the value of similarity metrics between potential matches out of two sets of objects. A combination of cooperative and competitive signal passing reinforces the final activation of neural network nodes corresponding to the best matches, while inhibiting the nodes corresponding to conflicting matches. This offers an advantage over traditional methods of identifying best matches, such as least squares.

Once the report-to-track association task is accomplished, sensor fusion can be done. The neural network approach focuses on fusing target kinematics, as other types of information (e.g. beacon identification, ESM signatures) are often uniquely obtained from their respective sensors and may be associated but not necessarily fused. Sensor data fusion is then one of combined association and fusion; new target reports are associated with the best possible master target track. Where possible similar information provided by the sensors and by target track positions are fused. A sequence of recent fused reports are associated with each track, and are updated periodically.

Display of fused target data is also a crucial component of this system. Our innovations in both report-to-track association and sensor fusion involve use of neural network algorithms.

2.0 Report-To-Track Association

Sensor data fusion leading to possible target identification, needs to work with each target as observed over time. The system uses report-to-track association, rather than static report correlation. Use of master target tracks allows prediction of where target locations will be, which will enhance report-to-track association.

2.1 Constraints Resulting from System Requirements Design and Analysis

Constraints governing the choice of the report-to-track algorithm selection and development:

- Work with multiple sensors: The methods selected is usable with several different types of sensors which may have different dimensionalities, different locations, different rates or types of target report access, etc. This suggests that the system should invoke several methods; i.e., report association based on beacon response or signature matching should be used where feasible as well as report-to-track matching using target and track kinematics.

- Computational throughput considerations: Advances in hardware and system software (including parallelizable systems) make possible more advanced algorithms, in a real-time environment. Nevertheless, the report-to-track association task has computational complexity on the order of $O(n x m_k x k)$, where n is the number of existing master target tracks and m_k is the number of new target reports from each of k sensors. Assume, for simplicity, batch processing of a sweep's worth of data as a group, where a typical sweep for a radar might be 4 seconds per cycle. Then all of the report-to-track associations need to be completed within about 4 seconds.

- Effective report-to-track matching under dense target conditions: The ideal approach to reconciling possible conflicts in report-to-track association under dense target conditions use as much information as possible in determining final associations. Optimally, a method can be found which allows the influence of additional target-descriptive information as well as target kinematics.

3.0 Cooperative-Competitive Neural Network

The cooperative-competitive neural network is well suited to several different applications. Its strength is that it is able to determine relationships between entities presented as input. Cooperative-competitive neural networks have been used with image understanding techniques since they are able to recognize important features in an image or in dynamic inputs, such as with automatic target recognition. Cooperative-competitive neural networks are also able to recognize one-to-one matches from many-to-many matches; a feature useful to target tracking [Maren et al., 1989 and 1990].

The cooperative-competitive neural network architecture is generally constructed with five logical layers of phases. Layer one stores initial inputs to the neural network. Layer two stores the current strength value of each node derived as a function of the input. The values in layer two are used to populate adjacent (competitive) nodes in the same neural network relation and excite corresponding (cooperative) neurons in other neural network relations. (Each relation may be a feature or type of data considered.) Layer three stores inhibitory or excitatory signals received from other neurons. Layer four applies these signals to the values in layer two. Finally, winning nodes are selected from the neural network indicating the most similar matches.

The cooperative-competitive neural network has been described extensively in Minsky and Maren [1990], Maren et al. [1990] and Minsky [1990]. A significant role in the neural network based sensor fusion system is performed by the cooperative-competitive neural network. It performs final refinement of conflicting matches between target tracks and target detections. Once final refinements are made for each sensor-derived position, these values may be fused into target track kinematics.

4.0 Tracker

The neural network based sensor data fusion system has developed an adaptive approach to the classic alpha/beta tracker, which allows the alpha and beta coefficients to be updated in real time, using target kinematic information provided by the predicted target position and the sensor data. While the neural network which accomplishes this adaptive updating is a classic feedforward neural network, innovations include use of distance metrics and variances between these metrics as input to the neural network. Once trained, the neural network providing updates for alpha and beta operates very fast and is suitable for real time target tracking applications.

A modified version of the cooperative-competitive neural network, using a voting neural network, for target identification/classification is being investigated, as well as a backpropagating Perception to assess target classes. In each case, the input is provided by a variety of existing target classification/identification processes.

5.0 Algorithm For Data Association

Several processing steps are taken before the cooperative-competitive neural network is used. Polar coordinates of data coming from the bus are converted to x, y and z coordinates. if the target track has had three or more detections velocity and acceleration are available and a prediction is made for the location of the target track at the time of each new target detection. A gate is created around that predicted point. (Velocity may be used alone in the prediction, if necessary, but the gate around the target track is made larger to account for increased prediction error.) Any new target detection falling within that gate will be associated with this target track as a preliminary match. However, many conflicts may remain between the target tracks and target detections.

The cooperative-competitive neural network is applied when other techniques are unable to resolve conflicts between new targets detections and existing target tracks. Conventional techniques such as gates around the predicted position are first used. If IFF information is available from the sensor, this may be used to further refine these matches. The matrix created by the target tracks and target detections is partitioned only to include conflicts.

Several matrices are derived from the time period represented in Figure 1. A complete matrix showing all representations is shown in Figure 1(b). The partitioned matrices which will be passed to the cooperative-competitive neural network are displayed in 1(c). partitioning the pairing matrix illustrates how computational complexity is reduced.

Computational benefits are much greater as target tracks and detections increase. Assuming three sensors acquire the same targets in Figure 1, the number of operations the cooperative-competitive neural network would use are 324 for the complete matrix. By partitioning the matrix only 117 operations for removing conflicts in target track 4 had no conflicts so the cooperative-competitive neural network is not required for this track.

6.0 Use of the Cooperative-Competitive Neural Network in Data Association

The cooperative-competitive neural network further refines the best pairing between existing target tracks and new target detections. One neural network relation is used for each dimension considered. A neural network is configured based upon the conflicting matches to be resolved.

Positional information, including the coordinates of the target detection and the predicted coordinates of the target track, is input into the neural network. The strength to each node is a function of the distance between the predicted position of the target and the actual position of the target detections. The distance between the predicted position of the target track and the target detection is inversely proportional, normalized between 0 and 1.

Inhibitions and/or excitations are used between neuron to determine a global winner in all the neural network relations. A strong neuron will inhibit competing neurons in the same neural network relation and excite corresponding neurons in another neural network relation. For example, corresponding neurons in y and z will have an excitatory effect on each other (i.e. the activation value of x will increase in proportion to the strength of y). The strongest neurons within the same x relation will have the strongest inhibitory effect on the other neurons. See Figure 2 for an illustration. The neuron with the strongest value among all neural network relations (x, y, and z) is selected as the winner and determined to be the closest target track/target detection pairing. The next strongest value will determine the next closest target tracks and target detection pair. This process will continue until no conflict exist between target tracks and target detections. If a target detection cannot be matched to a target, a new target track will be created.

For every target track/target detection matching problem, the cooperative-competitive neural network is reconfigured based upon the conflicts to be resolved. Neural network architecture is customized with the appropriate number of nodes based upon the target tracks and their potential matches in the pairing matrix. The strength of each neuron in the neural network is defined based upon the distance from its potential match.

For each sensor available, this data association with the cooperative-competitive neural network is performed, as needed. The output of the cooperative-competitive neural network represents the best position estimates for all target tracks from a single sensor. These position estimates from each of the J sensors must still be fused into a refined position estimate as shown in Figure 3.

7.0 Sensor Fusion

When data association has been completed, sensor fusion will be performed with a weighted sum of all different target positions. Based upon the confidence in each of the sensors, the values for range, azimuth and altitude are combined to obtain to refined target position.

Confidence values for the weighted sum are a function of the past performance of the sensor reports or prediction estimates. Investigation of a tracker which will use a neural network (currently a modified backpropagation neural network with recurrent connections) to update the confidences in the predicted and sensor-derived positions is continuing.

Without adapting predicted and sensor-derived positions online, the alpha/beta tracker worked well in the simulated and testing environment.

This backpropagation neural network is actually an unsupervised neural network. Since the model position of the target is unknown in an actual target tracking scenario, error is derived from a measure of the distances between the sensor-derived positions and the predicted position. Training is an on-line process with the neural network updating confidences with the frequency of training specified by an operator. In many situations, training iteration(s) are not necessary on every scan.

8.0 Simulation Results

The results of this project were tested on a Silicon Graphics high performance workstation. Testing involved the use of simulated data. Data was created with the following assumptions: 1) Sensors are co-located. However, adjusting for offsets in sensor position will be straightforward. 2) Sensors are synchronized and have the same scan rate. Eventually the plan is to use multi-tasking in the Ada language to handle the asynchronous data from different sensors.

Our current simulator was written to create target tracks with three dimensional coordinates and calculate the time when the target made a change of course. The maximum rate at which targets could be detected was based upon the 1553 bus speed *(30 Hz). Time (bus cycle) at which the target is detected was determined by the speed of the target set in the simulator. The position of the target (expressed in polar coordinates) was set up graphically so that target tracks could be set up rapidly into interacting scenarios.

This simulated sensor data association and fusion system was tested with several scenarios. One scenario tested the crossing of two targets. Another scenario modeled two targets flying together and then splitting into different directions. Finally, a dog fight scenario was used.

Once the model path of each target was established, zero-mean Gaussian noise could be added to the target when needed. Adding standard deviations of 10, 15 and 25 percent zero mean Gaussian noise, did not negatively affect target tracking in any of these scenarios.

9.0 Conclusion

The use of neural networks for a multi-sensor fusion system can provide better performance than comparable systems. The cooperative-competitive neural network has performed the tasks of sensor data association and sensor fusion in the system. Neural network architectures and training methods offer the flexibility and adaptability required to identify targets in rapidly changing environments. The neural network alpha/beta tracker offers some distinct advantages over conventional techniques. Together the sensor data association system with the neural network tracker with adaptable confidences and sensor fusion will be robust and efficient for future generations of naval air traffic control and radar systems.

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