Chapter 11

Retrospective Comments

The prerequisites for applying classical inference, Bayesian inference, Dempster-Shafer evidential theory, artificial neural networks, voting logic, and fuzzy logic data fusion algorithms to target detection, classification, and identification have been discussed. These data fusion techniques require expert knowledge, probabilities, or other information from the designer to define either:

- Acceptable Type 1 and Type 2 errors;
- *a priori* probabilities and likelihood functions;
- probability mass;
- neural network type, numbers of hidden layers and weights, and training data sets;
- confidence levels and conditional probabilities; or
- membership functions and production rules.

The information required to execute these algorithms is summarized in Table 11.1. Implementation of the data fusion algorithms is thus dependent on the expertise and knowledge of the designer (e.g., to develop production rules or define the artificial neural network type and parameters), analysis of the operational situation (e.g., to establish values for the Type 1 and Type 2 errors), applicable information stored in databases (e.g., to calculate the required probabilities or confidence levels), and the types of information provided by the sensor data (e.g., is the information adequate to calculate probability masses or differentiate among confidence levels?).

Table 11.1 Information needed to apply classical inference, Bayesian inference, Dempster-Shafer evidential theory, artificial neural networks, voting logic, and fuzzy logic data fusion algorithms to a target detection, classification, or identification application.

Data Fusion Algorithm	Required Information	Example
Classical inference	Confidence level.	95 percent, from which a confidence interval that includes the true value of the sampled population parameter can be calculated.
	Significance level α on which the decision to accept one of two competing hypotheses is made.	5 percent. If the *P*-value is less than α, reject H_0 in favor of H_1
	Acceptable values for Type 1 and Type 2 errors.	5 percent and 1 percent, respectively. The choice depends on the consequences of a wrong decision. Consequences are in terms of lives lost, property lost, opportunity cost, monetary cost, etc. Either the Type 1 or Type 2 error may be the larger of the two, depending on the perceived and real consequences.
Bayesian inference	*a prio*ri probabilities $P(H_i)$ that the hypotheses H_i are true.	Using archived sensor data or sensor data obtained from experiments designed to establish the *a priori* probabilities for the particular scenario of interest, compute the probability of detecting a target given that data are received by the sensor. The *a priori* probabilities are dependent on preidentified features and signal thresholds if feature-based signal processing is used or are dependent on the neural network type and training procedures if an artificial neural network is used.
	Likelihood probabilities $P(E\|H_i)$ of observing evidence *E* given that H_i is true as computed from experimental data.	Compare values of observables with predetermined or real-time calculated thresholds, number of target-like features matched, quality of feature match, etc. for each target in the operational scenario. Analysis of the data offline determines the value of the likelihood function that expresses the probability that the data represent a target type a_j.

Table 11.1 Information needed to apply classical inference, Bayesian inference, Dempster-Shafer evidential theory, artificial neural networks, voting logic, and fuzzy logic data fusion algorithms to a target detection, classification, or identification application (continued).

Data Fusion Algorithm	Required Information	Example
Dempster-Shafer evidential theory	Identification of events or targets $a_1, a_2, \ldots, a_n$ in the frame of discernment Θ.	Identification of potential targets, geological features, and other objects that can be detected by the sensors or information sources at hand.
	Probability masses m reported by each sensor or information source (e.g., sensors and telecommunication devices) for individual events or targets, union of events, or negation of events.	$m_{S1} = \begin{bmatrix} m_{S1}(a_1 \cup a_2) = 0.6 \\ m_{S1}(\Theta) = 0.4 \end{bmatrix}$ $m_{S2} = \begin{bmatrix} m_{S2}(a_1) = 0.1 \\ m_{S2}(a_2) = 0.7 \\ m_{S2}(\Theta) = 0.2 \end{bmatrix}$
Artificial neural networks	Artificial neural network type.	Fully connected multilayer feedforward neural network to support target classification
	Numbers of hidden layers and weights.	Two hidden layers, with the number of weights optimized to achieve the desired statistical pattern capacity for the anticipated training set size, yet not unduly increase training time
	Training data sets.	Adequate to train the network to generalize responses to patterns not presented during training
Voting logic	Confidence levels that characterize sensor or information source outputs used to form detection modes.	Sensor A output at high, medium, and low confidence levels (i.e., A_3, A_2, and A_1, respectively); Sensor B output at high, medium, and low confidence levels; Sensor C output at medium and low confidence levels.
	Detection modes.	Combinations of sensor confidence level outputs that are specified for declaring valid targets. Based on ability of sensor hardware and signal processing to distinguish between true and false targets or countermeasures.
	Boolean algebra expression for detection and false alarm probabilities.	For a three-sensor, four detection mode system, System $P_d = P_d\{A_1\}\ P_d\{B_1\}\ P_d\{C_1\} + P_d\{A_2\}\ P_d\{C_2\} + P_d\{B_2\}\ P_d\{C_2\} + P_d\{A_3\}\ P_d\{B_3\} - P_d\{A_2\}\ P_d\{B_2\}\ P_d\{C_2\}$.

Table 11.1 Information needed to apply classical inference, Bayesian inference, Dempster-Shafer evidential theory, artificial neural networks, voting logic, and fuzzy logic data fusion algorithms to a target detection, classification, or identification application (continued).

Data Fusion Algorithm	Required Information	Example
Voting logic (continued)	Confidence level criteria or confidence level definitions.	Confidence that sensors are detecting a real target increases, for example, with length of time one or more features are greater than some threshold, magnitude of received signal, number of features that match predefined target attributes, degree of matching of the features to those of preidentified targets, or measured speed of the potential target being within predefined limits. Confidence that radio transmissions or other communications are indicative of a valid target increases with the number of reports that identify the same target and location.
	Conditional probabilities that link the inherent target detection probability $P_d'\{A_n\}$ of Sensor A at the n^{th} confidence level with the probability $P_d\{A_n\}$ that the sensor is reporting a target with confidence level n.	Compute using offline experiments and simulations; also incorporate knowledge and experience of system designers and operations personnel.
	Logic gate implementation of the Boolean algebra probability expression.	Combination of AND gates (one for each detection mode) and OR gate.
Fuzzy logic	Fuzzy sets.	Target identification using fuzzy sets to specify the values for the input variables. For example, five fuzzy sets may be needed to describe a particular input variable, namely very small (VS), small (S), medium (M), big (B), and very big (VB). Input variables for which these fuzzy sets may be applicable include length, width, ratio of dimensions, speed, etc.
	Membership functions.	Triangular or trapezoidal shaped. Lengths of bases are determined through offline experiments designed to replicate known outputs for specific values of the input variables.
	Production rules.	IF-THEN statements that describe all operating contingencies. Heuristically developed by an expert based on experience in operating the target identification system or process.
	Defuzzification.	Fuzzy centroid computation using correlation-product inference.


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