Application of Intent Inference for Air Defense and Conformance Monitoring

PEK HUI FOO
GEE WAH NG
KHIN HUA NG
RONG YANG

Intent inference involves the analysis of actions and activities of a target of interest to deduce its purpose. This paper proposes an approach for intent inference based on aircraft flight profile analysis. Simulation tests are carried out on flight profiles generated using different combinations of flight parameters. In each simulation test, Interacting Multiple Model-based state estimation is carried out to update the state vectors of the aircraft being monitored. Relevant variables of the filtered flight trajectory are subsequently used as inputs for a Mamdani-type fuzzy inference system. Research on two applications is reported. The first application involves the determination of the likelihood of weapon delivery by an attack aircraft under military surveillance. Test results verify that the method is feasible and is able to provide timely inference. By extending the method to take the environmental context of the tracked aircraft into consideration when executing the inference process, it is likely that the military defenders would be able to raise their alert earlier against potential adversaries. This would provide them with more time to react and devise pre-emptive counteraction. The second application concerns conformance monitoring in air traffic control systems. Experimental results show that the proposed solution can be used to assist air traffic control system operators in determining if aircraft navigate according to planned trajectories. Consequently, corrective action can be taken on detection of anomalous behavior. A brief discussion on extending the proposed method to deal with multiple aircraft is also presented.

Manuscript received September 16, 2007; released for publication October 13, 2008.

Refereeing of this contribution was handled by Pierre Valin.

Authors' address: DSO National Laboratories, 20 Science Park Drive, Singapore 118230, Singapore.

1557-6418/09/$17.00 © 2009 JAIF

1. INTRODUCTION

The human brain has remarkable capabilities in perception and reasoning. However, the amount of complex data/information that can be processed by the human brain is constrained by the limited memory capacity. Hence, computational tools are necessary to provide cognitive aid to the human brain in attaining better performance in intellectual tasks, such as decision making.

Intent inference is about analyzing the actions and activities of an opponent or a target of interest to obtain a conclusion (prediction) on its purpose [3, 10, 18, 24]. Generally, data (collectively called observables) concerning the opponent are first collected from available sources. Next, the data are fused to obtain useful information. Finally, the fused information is utilized to derive the inferred intent of the opponent. It is desirable that intent inference be able to provide three kinds of hypotheses about an opponent's objective [3, 18]:

- Descriptive intent inference—provides insight into the motivations behind preceding actions;
- Predictive intent inference—anticipates the opponent's future actions given his deduced goals;
- Diagnostic intent inference—detects differences between predicted and observed actions to reveal possible errors.

Accurate prediction of an opponent's intention, actions and reactions would be useful for the purpose of devising effective responses to his actions, as well as planning for one's own operations.

Intent inference has been used in applications such as intelligent transportation systems (infer and detect a driver's intent [36]) and air traffic management (ATM) (predict the future trajectory of an air vehicle and the states of nearby aircraft [20, 42]). Other applications include the medical domain, recommender systems, tutoring systems and team intent identification [18].

In this paper, we report our research on two applications of intent inference [9, 25]. The first task is to determine the intent of the pilot (equivalently, the flight mission) of an aircraft being tracked by a military surveillance system [25]. The second involves conformance monitoring in air traffic control (ATC) systems [31].

This paper is organized as follows. Section 2 provides a general discussion on intent inference and a brief review on related work from the research literature. Section 3 describes our proposed fuzzy logic approach for intent inference based on the analysis of flight profiles for attack aircraft. In addition, the environmental context of the tracked aircraft is taken into consideration during the execution of the inference process. The impact of this additional factor on the inference outcome is investigated. Four different test scenarios are used to evaluate the feasibility of the proposed method. Section 4 is focussed on conformance monitoring in ATC/ATM systems. Section 5 presents simulation tests and results.

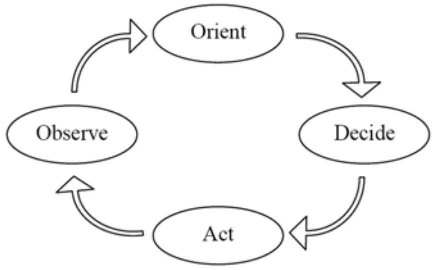

Fig. 1. The OODA Loop.

Section 6 gives a discussion on handling an approach by multiple aircraft. Section 7 provides a summary on this paper.

2. INTENT INFERENCE

The *Boyd Control Loop* (also called *Boyd's Decision Loop* or the *Observe, Orient, Decide, and Act* (OODA) *Loop*) [11, 27] is a popular model that has been used for formalizing concepts of tactical command and decision making. It describes human and organizational behavior as a continuous, iterative and cyclic process of *Observation* (represents event perception), *Orientation* (corresponds to the process of memory and cognition, the activity that provides environmental context and individual expectations), *Decision* (describes the process of cognitive comparison) and *Action* (equals the resulting behavior). In particular, the function Orientation shapes the way the other functions, Observation, Decision and Action, are done.

The emphasis of this model is placed on shortening the cycle to perform the Observe to Act loop (see Fig. 1):

- Observe—gather data from the environment via human and related senses,
- Orient—gain situation awareness and perform situation and impact/threat assessment based on the information derived from the data obtained,
- Decide—respond to situation and work out follow-up actions,
- Act—execute the planned response,

to the extent that the opponent cannot respond in time to carry out countermeasures, thus gaining superiority in the engagement. The OODA Loop can also be applied to computer-assisted cognition.

An intent inference system provides reasoning about the opponent's intent, mission objective, or motivation. By nature of the inference mechanism, the intent inference system will also be able to provide prediction on the opponent's possible future actions or activity according to the inferred intent. Thus, it serves as useful decision support to the decision maker. In this way, the inference system not only contributes to better situation awareness and aids in resolving ambiguity that arises from multi-source fusion, but further assists the decision maker in his cognitive task and helps in shortening the decision making process.

Intent inference is a relatively young and challenging research area as compared to the maturing lower level data fusion. Emerging interest in the application of this research area can be found in the military arena [3, 37] and antiterrorism [12, 16]. Generally, intent and activity inference requires a cognitive architecture with knowledge-based modeling. Inputs to the inference system are information gathered through intelligent autonomous agents or provided by multiple sensing sources, including reports from human intelligence. Through modeling, the structure and pattern of opponent entities, as well as their behavior and relationships, are captured. The focus of the inference mechanism is on contextual and relational reasoning as opposed to single entity reasoning at lower level fusion processes. The inference mechanism may be based on a rule-based system or a more dynamic reasoning system such as Bayesian networks. In this paper, a fuzzy inference system (FIS), also known as a fuzzy-rule-based system, is used.

2.1. Related Research Work

A method for pilot intent inference in real-time was investigated in [19]. It was based on plausible models of intent and a process for identifying models that matched observed aircraft motion best. The models were ranked based on their correlation with measured aircraft motion. The highest ranked plausible models of intent made up the best estimate of the aircraft intent. Sequences of actions were executed to infer guidance and navigation task intents of the tracked aircraft. The inferred intent was then used as a basis for trajectory prediction.

The authors of [41] proposed an intent-based trajectory prediction algorithm to carry out maneuvering aircraft tracking, aircraft intent inference and trajectory prediction. A hybrid estimation algorithm was used for estimating the states and flight mode of the aircraft. Intent inference was posed as a maximum likelihood problem. Pilot intent inference was obtained via the combination of the state and flight mode estimates, air traffic control regulations, the flight plan of the aircraft and environment information. The inferred intent and the aircraft motion (state and flight mode estimates) were used for the computation of trajectory prediction. The proposed algorithm was tested and analyzed through simulations in different scenarios representative of aircraft operations.

In [1], a hybrid system model of intent inference was constructed for air traffic controllers. An algorithm based on the Interacting Multiple Model (IMM) Kalman filter (the State Dependent Transition Hybrid Estimation algorithm) was implemented for state estimation, as well as the generation of residuals (discrepancies) between the observed aircraft states and the expected aircraft states. The residual mean was generated based on probabilistic methods. The proposed model was applied to an example problem on conformance monitoring. A statistical test was carried out on the residual means for both the conformance monitoring model and the actual aircraft system to obtain a conclusion/decision on conformance or non-conformance.

Conformance monitoring in air traffic control is a relatively new application of intent inference. Some research work based on fault detection has been done in this area [30–35] and will be discussed in Section 4.

2.2. Inference Mechanism

Classification is the process of inferring the concept behind an available collection of observations. This task covers any context in which some decision or forecast is made based on available information. It involves the establishment of a mapping from a measurement (an observation) space to a decision space. Input measurement/observation data is assigned into one or more predetermined classes based on the selection/extraction, as well as the processing or analysis, of significant features or attributes. Some commonly used approaches to classification are briefly discussed below [17].

2.2.1. Statistical Approach

Statistical (or decision theoretic) classifiers are generally characterized as having an explicit underlying probabilistic model. In a parametric classification procedure, a set of characteristic measurements (features) are extracted from the input data, and are used to assign each feature vector to one of the predetermined classes. Features are assumed to be generated by a state of nature, the underlying model represents a state of nature, set of probabilities, or probability density functions, that are conditional on the classes.

There are cases when there is insufficient prior information available, or when it is not necessary, to make assumptions about the distribution associated with the feature vector in the different classes. Under such circumstances, it is possible to use non-parametric estimation of the pdf involved to build distribution-free methods of classification (that is, non-parametric classifiers).

Statistical classifiers generally work reasonably well for problems in which structures are not deemed significant.

2.2.2. Neural Network Approach

A neural network assumes that a set of input data and their correct classifications are given. The architecture of a neural net includes layers of interconnected nodes. It is characterized by a set of weights and activation functions which determine the transmission of information from the input layer to the output layer. The training data is used to train the neural network and adjust the weights until the correct classifications are obtained. The complete network generally represents a complex set of interdependencies, which may incorporate an arbitrary degree of nonlinearity.

Neural networks are suitable for solving problems with a large amount of features and classes. They can be applied to problems that involve generalization, parallel processing, or discrimination among classes with highly nonlinear boundaries.

2.2.3. Fuzzy Logic Approach

Classification is often done with some degree of uncertainty. In problems with data that are noisy and distorted, complications can arise and lead to ambiguous situations in which classified data may belong in some degree to more than one class, or the classification outcome itself may be in doubt. Fuzzy logic (or fuzzy set theory) can be introduced to deal with such problems. In fuzzy classification, an input data entity is assigned a membership value in the interval $[0, 1]$ in each predetermined class.

2.3. Proposed Approach

We propose that intent inference be carried out via a fuzzy logic approach (conceptual information on fuzzy logic used in this paper [15, 38, 39] is given in the Appendix). The main reasons that motivate the use of the proposed approach are as follows.

Firstly, compared to statistical and probabilistic methods used in most related research work, fuzzy logic techniques are particularly suitable for modeling problems with inherent imprecision properties [11, 23]. The problems to be discussed in this paper involve observation/information associated with human cognitive processes such as thinking and reasoning, in which uncertainties and imprecision are usually inherent. Therefore, it is appropriate to use fuzzy logic to deal with these problems.

Secondly, fuzzy logic techniques are useful for the fusion of information from multiple input sources and the application of heuristics to determine the overall status of the inputs [7]. Hence, for each problem in this paper, the information obtained from tracking the subject aircraft can be fused to determine the pilot intent, which is required by the surveillance/monitoring system users concerned for decision making.

Thirdly, implementation of fuzzy logic is simple, fast and efficient [21, 38]. This would be useful for problems in which computational load/time is a critical factor, such as the two problems of interest here. For the first task on air defense, it is essential to take preemptive action against potential adversaries as quickly as possible, in order to avert possible attacks. For the second problem on conformance monitoring in air traffic control systems, it is important to minimize the delay in correcting any deviant aircraft behavior that is detected.

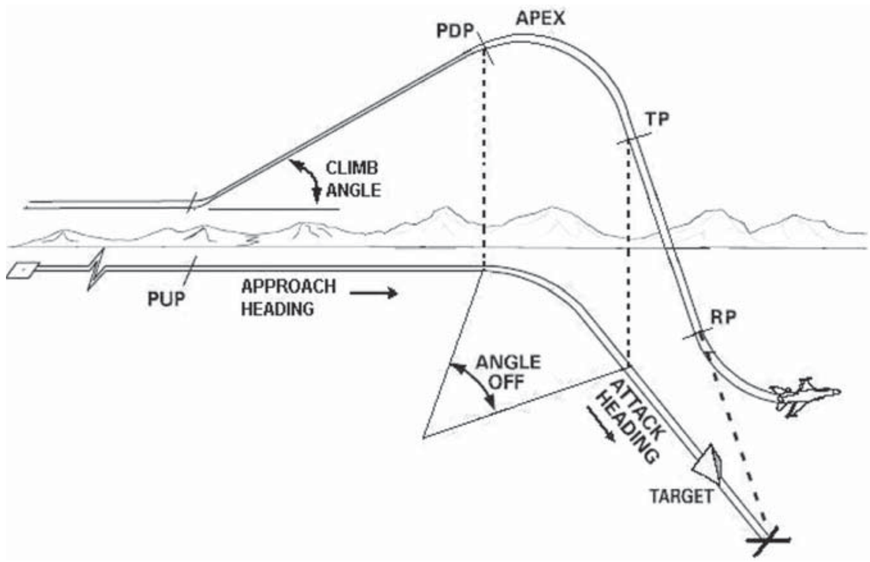

Fig. 2. Flight profile for offset pop-up delivery.

A fuzzy inference system is a computing framework based on the concepts of fuzzy set theory, fuzzy rules and fuzzy reasoning (an inference procedure which derives conclusions from a set of fuzzy rules and available information) [15]. The basic structure of a fuzzy inference system comprises three conceptual components:

- rule base—contains a selection of fuzzy rules,
- database—defines the membership functions used in the fuzzy rules,
- reasoning mechanism—performs the inference procedure upon the rules and known facts to derive a reasonable output or conclusion.

The inference mechanism used in this paper is based on the widely accepted Mamdani's fuzzy inference method [15], which was one of the first control systems built using fuzzy set theory. It was proposed as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators.

The Mamdani-type FIS used here is generated using the MATLAB Fuzzy Logic Toolbox [38, 39]. The fuzzy inference process has five parts, namely, fuzzification of the input variables, application of the fuzzy operator in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules, and defuzzification. Details on each part of the fuzzy inference process implemented for the two applications discussed in this paper are provided in Sections 3 and 4.

3. WEAPON DELIVERY BY ATTACK AIRCRAFT

Effective intent inference will greatly enhance the defense capability of a military force in taking preemptive action against potential adversaries. It serves as a form of advance warning in the prevention of a crisis (for instance, enemy attack) or facilitates the moderation of the impact of such a crisis. For an air defense system, the ability to accurately infer the likelihood of a weapon delivery by an attack aircraft is critical.

The type of weapon delivery for attack aircraft considered in this paper is offset pop-up delivery. The definitions for some terms pertaining to this form of weapon delivery are stated below. Section 3.1 provides a brief description of offset pop-up delivery [40].

- Pop Point (PUP)—a position at which the pop-up attack is initiated, the point where climb is initiated.
- Pull-Down Point (PDP)—a maneuver point where one transitions from the climbing to the diving portion of a pop-up delivery.
- Apex—the highest altitude in the pop-up delivery profile.
- Track Point (TP)—the starting point of tracking prior to arriving at planned release altitude.
- Release Point (RP)—the point at which weapon is released.

A tracked aircraft is considered to have constant speed, with the velocity components in the horizontal plane (parallel to ground) and the vertical axis (parallel to altitude) varying in different phases of the trajectory. In this application, altitude, distance and velocity are measured in feet above ground level (AGL), feet and knots respectively, unless otherwise stated.

3.1. Typical Offset Pop-up

The pop-up approach heading, as shown in Fig. 2 [8], is at an angle (varies with the planned climb angle) from 15° to 90° from the final attack heading. This allows the pilot to acquire the target as soon as possible and maintain visual contact until weapon delivery is completed.

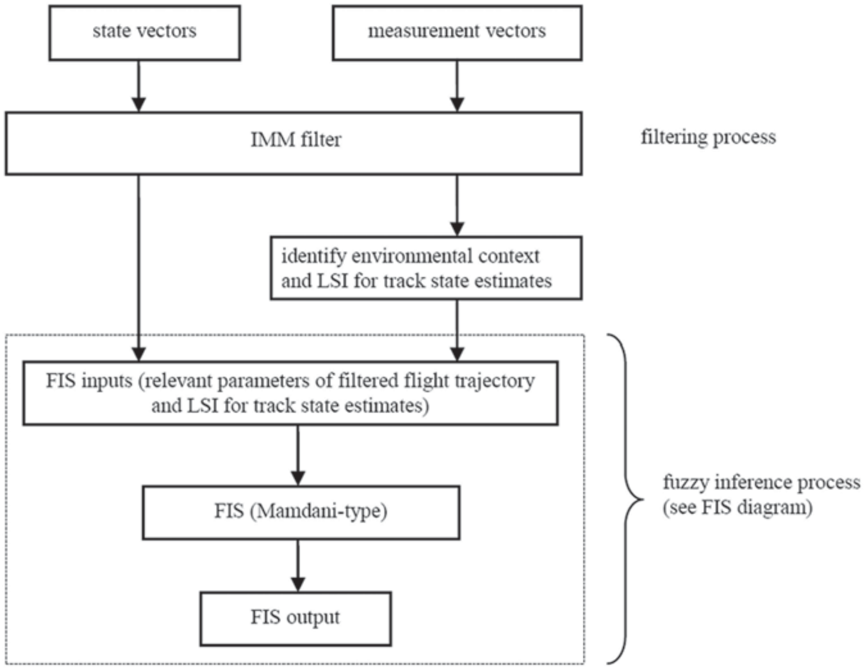

Fig. 3. Overview of proposed system.

The pilot initiates the pop-up over a preplanned pop point at a minimum airspeed of 450 knots calibrated airspeed (KCAS). He selects his desired power, makes a 3–4 G wings-level pull to the desired climb angle and initiates a chaff/flare program. After popping, he has to maintain the planned climb angle and monitor the altitude gained.

When approaching the preplanned pull-down altitude, the pilot makes an unloaded[1] roll in the direction of the target. He then performs a 3–5 G pull-down to intercept the planned dive angle. Interception of the planned dive angle while pointed at the aim-off point is a critical factor in attaining preplanned delivery parameters. It is usually acceptable to have minor deviations in the attack heading.

During the maneuver, corrections are made to compensate for minor errors in the pop point or unexpected winds in the climb to the apex at the planned altitude. The planned apex altitude is normally achieved about half way through the pull-down maneuver.

For safety reasons, a pilot would most probably abort a pop-up attack immediately if at least one of the following conditions arises:

- the actual dive angle exceeds the planned one by more than 5°,
- the airspeed goes below 350 KCAS (300 KCAS above 10000 feet AGL).

The occurrence of such conditions would result in inaccuracy in the impact point of the released weapon.

3.2. Process and Techniques

Our proposed procedure for inferring the possibility of weapon delivery by a tracked attack aircraft, based on flight profiles, is given below.

Procedure 1

1. For an aircraft being tracked, record its state information (sensor measurement data) through observation.
2. Apply the IMM algorithm [22, 24] to update the track state estimates.
3. For each track state estimate, use the position components to identify the environmental context and hence the corresponding location sensitivity index (LSI) (details in Sections 3.2.1 and 5.1).
4. Fuzzy inference process
   a. Input
      i. relevant parameters of the filtered flight trajectory, and
      ii. LSI obtained in Step 3,
      to a Mamdani-type fuzzy inference system gener ated using the MATLAB Fuzzy Logic Toolbox [38, 39].
   b. Output produced by the FIS is the inferred possibility of weapon delivery by the tracked aircraft.

[1]In aeronautics, the *lift* on an aircraft is the component of total air force acting on the aircraft which is perpendicular to the direction of flight and is normally executed in an upward direction. The *load factor* is the ratio of the lift on an aircraft to the weight of the aircraft, which is expressed in multiples of *G*, with 1 G representing conditions in straight and level flight.

Unloaded: the situation in which the load factor is 0 G, where every occupant of an aircraft experiences a feeling of weightlessness.

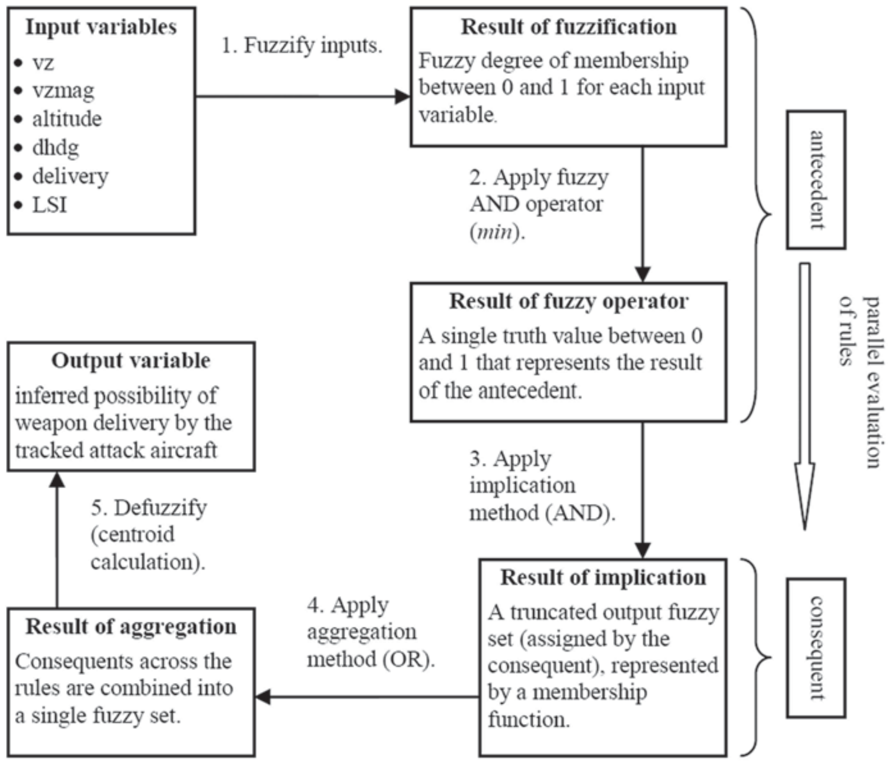

Fig. 4. Fuzzy inference system.

An overview of the system for the proposed approach is shown in Fig. 3. The entire fuzzy inference process is shown in Fig. 4. The following subsections provide details on the fuzzy inference process.

3.2.1. Fuzzification of the Input Variables

In the first step, each input variable is a crisp/non-fuzzy numerical value within its universe of discourse and is assigned a linguistic value in the interval $[0,1]$ via a membership function. The input variables considered in the current application are obtained from kinematic parameters of the filtered flight trajectory. Elaboration on each of the input variables, with respect to the tracked aircraft, is given below.

The first variable is the velocity along the vertical axis (abbreviated *vz*). It is classified as either positive (denoted by "> 0") or negative (denoted by "< 0"), indicating either upward or downward motion respectively. The second variable is the magnitude of vz (abbreviated *vzmag*). The third variable is the altitude. The fourth variable is an indicator for the occurrence of a change in heading (measured in radians, abbreviated *dhdg*) during the time interval between consecutive scans. A change in heading is considered to have occurred when the difference in heading between two consecutive records along the filtered flight trajectory exceeds a chosen threshold value ($\pi/180$ radians in the current application). The fifth variable is an indicator for the likelihood of a weapon delivery (abbreviated *delivery*) by the tracked aircraft. A weapon delivery is considered unlikely when at least one of the following conditions occurs:

- the actual dive angle exceeds the planned one by more than 5°,
- the airspeed goes below 350 KCAS (300 KCAS above 10000 feet AGL).

The sixth variable is an index representation of the environmental context of the tracked aircraft, named *location sensitivity index* (abbreviated *LSI*). The LSI is based on the degree of sensitivity of the spatial domain in which the tracked aircraft is traveling. High LSI corresponds to highly sensitive locations, including vicinities of critical infrastructure such as government establishments. Low LSI corresponds to locations with low sensitivity, including regions that are remote or not habitable.

Figs. 5 to 10 show the membership functions for the six input variables. Table I shows the symbols and their corresponding linguistic values for membership functions (where applicable).

TABLE I
Symbols used for Membership Functions

Symbol	VL	L	M	H	VH
Linguistic value	Very Low	Low	Medium	High	Very High

The number of levels for the linguistic values for membership functions can vary according to the amount

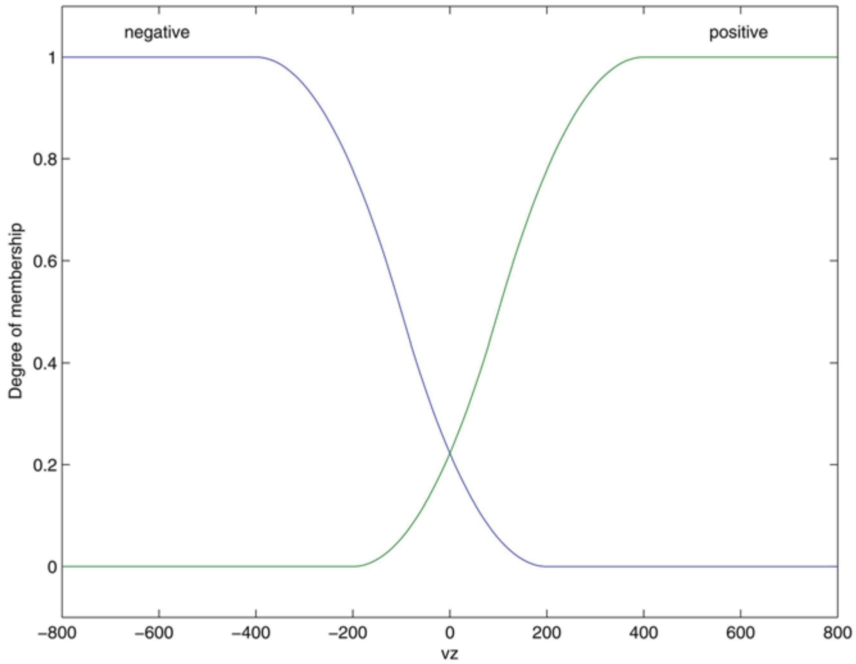

Fig. 5. Membership functions of “vz.”

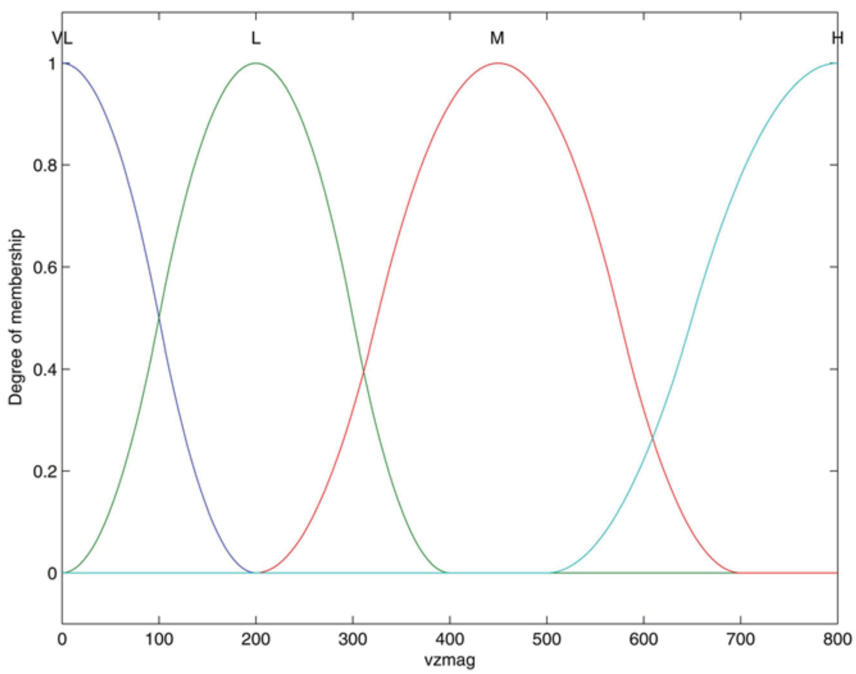

Fig. 6. Membership functions of “vzmag.”

of information available. Labels that are more descriptive can be used for various levels of linguistic values of a variable. An example is to use words such as fast, slow and constant when labeling different degrees of membership for variables related to velocity/speed.

3.2.2. Application of Fuzzy Operators

After fuzzification of the inputs, the degree to which each part of the antecedent is satisfied for each rule is known. When an antecedent of a given rule has multiple parts, a fuzzy operator (such as those defined in the Appendix) has to be applied to the multiple membership values from fuzzified input variables, in order to obtain one single truth value. This output value (which lies in $[0,1]$) represents the result of that antecedent for that rule and will be applied to the output function.

3.2.3. Application of Implication Method

For each rule, apply a weight (1 is used in this paper) to the single truth value given by the antecedent. Then implement the implication on this weighted value using

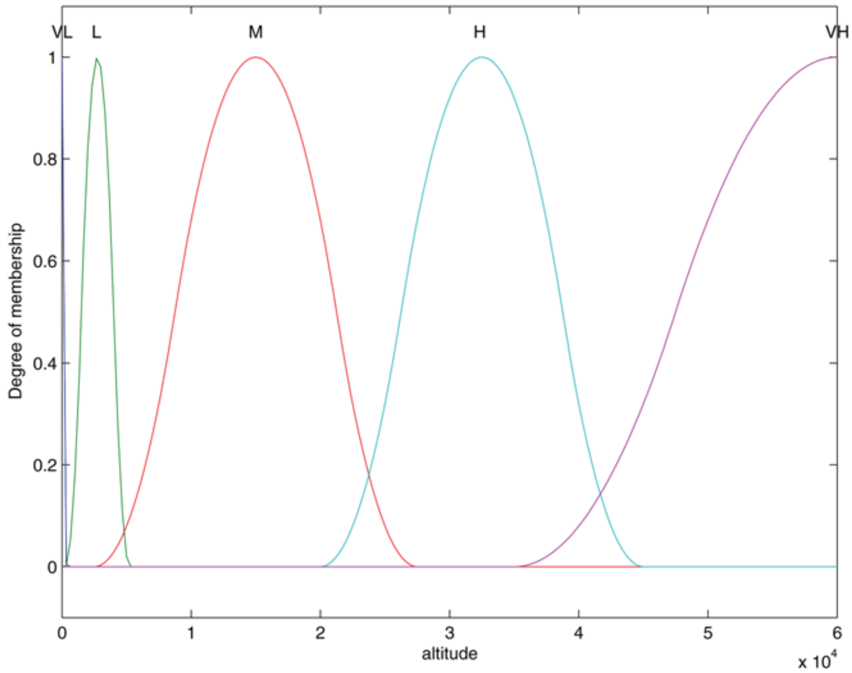

Fig. 7. Membership functions of "altitude."

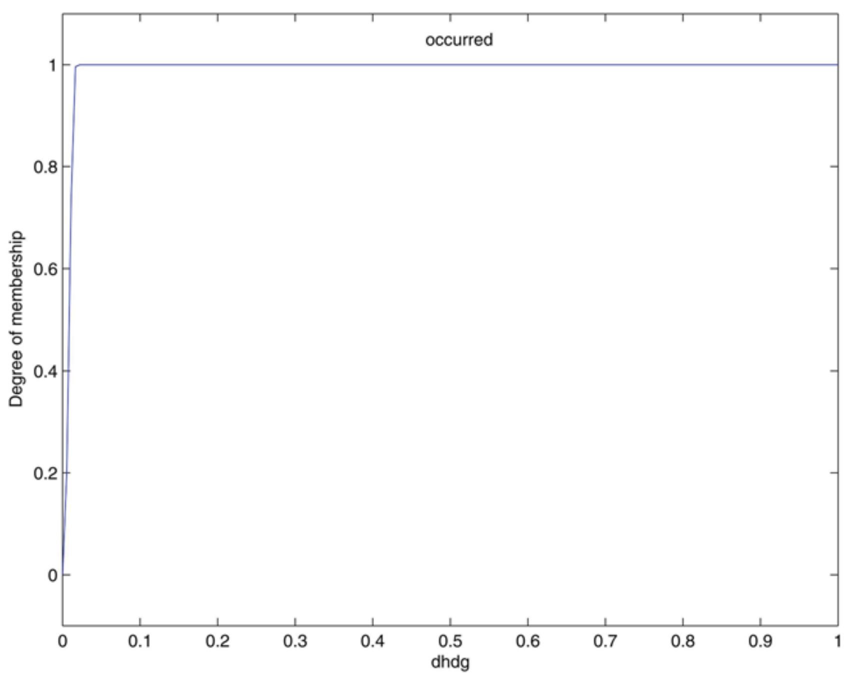

Fig. 8. Membership function of "dhdg."

the built-in AND method: min (minimum) function [38, 39]. The implication process yields an output fuzzy set (assigned by the consequent) which is truncated to the level of the weighted truth value of the antecedent. The rules used in the current application are listed in Table II. They are based on the expected characteristics of the motion along an offset pop-up delivery profile.

Fig. 11 shows the membership functions for the output variable (inferred possibility of weapon delivery by the tracked attack aircraft, abbreviated *pos*). The complexity of the rules can be modified according to the amount of information available.

3.2.4. Aggregation of All Outputs

It is necessary to determine an approach to combine the rules in a fuzzy inference system in order to reach a decision/conclusion. The output fuzzy sets of each rule (obtained via the preceding implication method) are unified to form a single output fuzzy set, whose membership function assigns a weighting for every

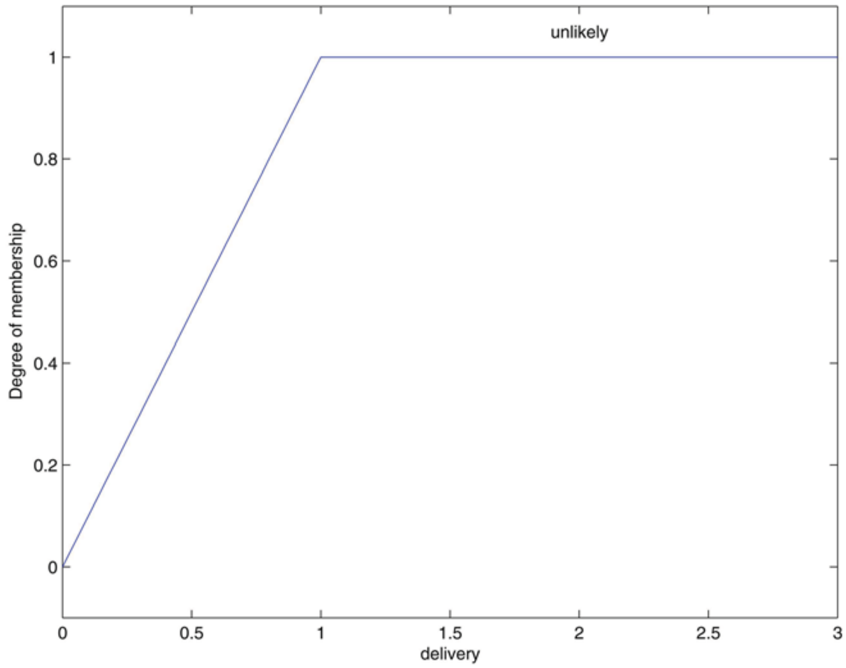

Fig. 9. Membership function of "delivery."

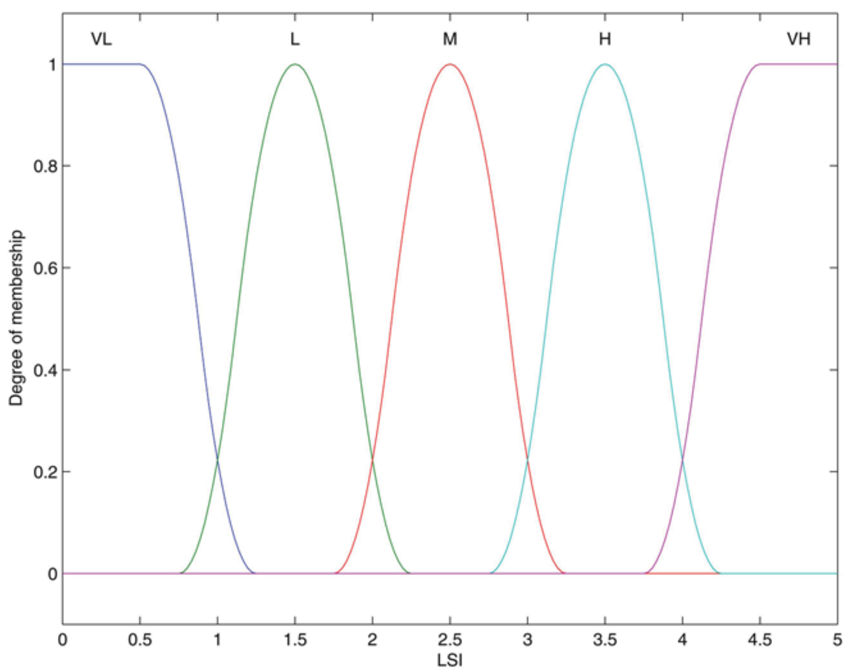

Fig. 10. Membership functions of "LSI."

output value. The aggregation process inputs are the truncated output membership functions returned by the preceding implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable. This paper utilizes the built-in OR method: max (maximum) function [38, 39] for the aggregation process. Therefore, the final membership function value is given by the maximum value among the consequent membership function values for each of the rules in the fuzzy inference system.

3.2.5. Defuzzification

In the last step of the fuzzy inference process, let F denote the output fuzzy set of the preceding aggregation process and Z denote the universe of discourse that F is in. Let $\mu_F(\cdot)$ be the aggregated output membership function representing F. Defuzzification of F yields the output of the fuzzy inference system, which is a single crisp/non-fuzzy number [15]. The built-in method of centroid calculation [38, 39] is used in this paper. The defuzzified output, z_{COA}, is the center of area under

TABLE II
Rules for Fuzzy Inference System (Weapon Delivery by Attack Aircraft)

R1.	(altitude is VL) $\rightarrow$ (pos is VL).
R2.	($vz > 0$) & (dhdg is NOT occurred) & (LSI is VL) $\rightarrow$ (pos is L).
R3.	($vz > 0$) & (dhdg is NOT occurred) & (LSI is L) $\rightarrow$ (pos is L).
R4.	($vz > 0$) & (dhdg is NOT occurred) & (LSI is M) $\rightarrow$ (pos is M).
R5.	($vz > 0$) & (dhdg is NOT occurred) & (LSI is H) $\rightarrow$ (pos is M).
R6.	($vz > 0$) & (dhdg is NOT occurred) & (LSI is VH) $\rightarrow$ (pos is H).
R7.	($vz > 0$) & (vzmag is L) & (dhdg is occurred) & (LSI is VL) $\rightarrow$ (pos is L).
R8.	($vz > 0$) & (vzmag is L) & (dhdg is occurred) & (LSI is L) $\rightarrow$ (pos is M).
R9.	($vz > 0$) & (vzmag is L) & (dhdg is occurred) & (LSI is M) $\rightarrow$ (pos is M).
R10.	($vz > 0$) & (vzmag is L) & (dhdg is occurred) & (LSI is H) $\rightarrow$ (pos is H).
R11.	($vz > 0$) & (vzmag is L) & (dhdg is occurred) & (LSI is VH) $\rightarrow$ (pos is H).
R12.	($vz > 0$) & (vzmag is VL) & (dhdg is occurred) & (LSI is VL) $\rightarrow$ (pos is M).
R13.	($vz > 0$) & (vzmag is VL) & (dhdg is occurred) & (LSI is L) $\rightarrow$ (pos is M).
R14.	($vz > 0$) & (vzmag is VL) & (dhdg is occurred) & (LSI is M) $\rightarrow$ (pos is H).
R15.	($vz > 0$) & (vzmag is VL) & (dhdg is occurred) & (LSI is H) $\rightarrow$ (pos is H).
R16.	($vz > 0$) & (vzmag is VL) & (dhdg is occurred) & (LSI is VH) $\rightarrow$ (pos is VH).
R17.	($vz < 0$) & (altitude is NOT VL) & (delivery is NOT unlikely) & (LSI is VL) $\rightarrow$ (pos is M).
R18.	($vz < 0$) & (altitude is NOT VL) & (delivery is NOT unlikely) & (LSI is L) $\rightarrow$ (pos is H).
R19.	($vz < 0$) & (altitude is NOT VL) & (delivery is NOT unlikely) & (LSI is M) $\rightarrow$ (pos is H).
R20.	($vz < 0$) & (altitude is NOT VL) & (delivery is NOT unlikely) & (LSI is H) $\rightarrow$ (pos is VH).
R21.	($vz < 0$) & (altitude is NOT VL) & (delivery is NOT unlikely) & (LSI is VH) $\rightarrow$ (pos is VH).
R22.	($vz < 0$) & (delivery is unlikely) & (LSI is VL) $\rightarrow$ (pos is L).
R23.	($vz < 0$) & (delivery is unlikely) & (LSI is L) $\rightarrow$ (pos is M).
R24.	($vz < 0$) & (delivery is unlikely) & (LSI is M) $\rightarrow$ (pos is M).
R25.	($vz < 0$) & (delivery is unlikely) & (LSI is H) $\rightarrow$ (pos is H).
R26.	($vz < 0$) & (delivery is unlikely) & (LSI is VH) $\rightarrow$ (pos is H).

$\mu_F(\cdot)$, defined by

$$z_{COA} = \frac{\int_Z \mu_F(z) z\, dz}{\int_Z \mu_F(z) dz}.$$

4. CONFORMANCE MONITORING

In conventional air traffic control and air traffic management operations, the controller creates a visualization of the current and future state dynamics of all aircraft under his control. For each individual aircraft, the controller determines if its observed behavior conforms to the expected or planned path [30, 35]. Unintentional deviations can result from noise in the surveillance systems, atmospheric effects and dynamics of the aircraft navigation systems. Such deviations can be used as threshold values in the definition of a "conformance region." An observed flight profile that lies within the region would be considered conforming, while one that lies beyond the region would be considered non-conforming. In the latter case, knowledge of the conformance status provides a basis for the air traffic controller to implement rectifying measures for the aircraft concerned.

In [31], an analysis framework was developed for the purpose of investigating issues pertaining to conformance monitoring in ATC/ATM. The conformance monitoring task was put forward as a fault detection problem. Fault detection and isolation techniques were used to determine if observable aircraft states were consistent with behavior that was normal (that is, conforming) or abnormal (that is, non-conforming). In other words, non-conforming behavior of an aircraft was regarded as a "fault" to be detected in the ATC/ATM system. The proposed framework comprised the following components:

- conformance basis— basis from which expected state behaviors of an aircraft are generated and against which observed behaviors of the subject aircraft are compared;
- actual system representation— key elements that execute instructions that form the communicated conformance basis;
- conformance monitoring model— generates expected state behaviors against which observed state behaviors are to be compared (requires appropriate level of fidelity to carry out effective conformance monitoring);
- conformance monitoring functions— determine at any time if observed state behaviors are consistent with expected state behaviors that are output by the conformance monitoring model.

The framework was implemented for several conformance monitoring tasks in air traffic control [32–34].

Enhancement and/or improvement of techniques for conformance monitoring is of much interest because of its importance in proper operation of ATC/ATM systems. In addition, there is much awareness of potential hazards to the air transport system posed by non-conforming aircraft that deviate from expected traffic patterns.

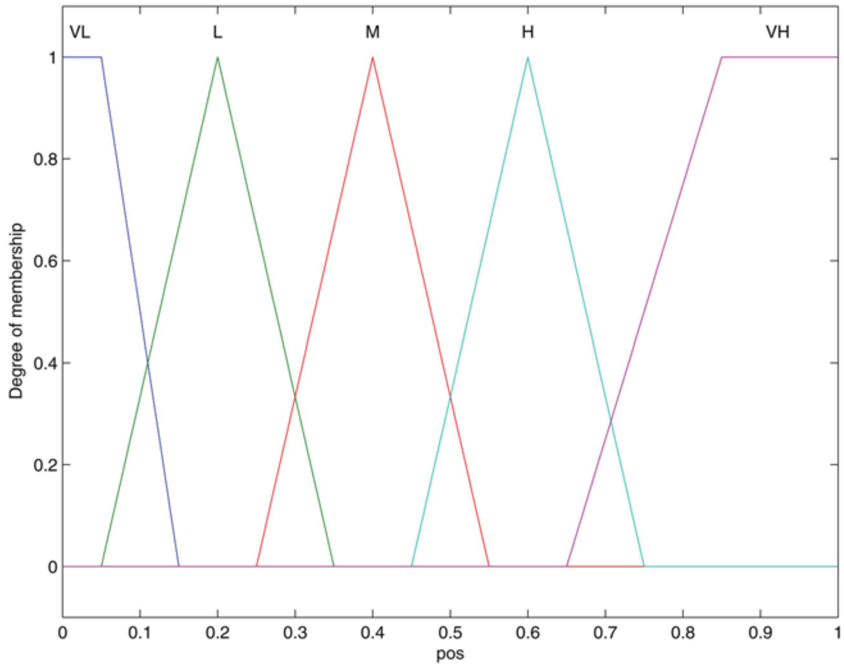

Fig. 11. Membership functions of "pos."

In order to maintain the safety, security and efficiency of ATC/ATM systems, timely detection of nonconforming behavior in aircraft is essential. Our objective in this application is to use a fuzzy inference approach to determine if a tracked aircraft is navigating within conformance limits.

4.1. Process and Techniques

The proposed procedure (a slight modification of Procedure 1 in Section 3.2) for inferring the possibility of non-conformance in the behavior of a tracked aircraft is stated below.

Procedure 2

1. For an aircraft under surveillance, record its state information (sensor measurement data) through observation.
2. Apply the IMM algorithm [22, 24] to update the track state estimates.
3. Fuzzy inference process
   a. Input relevant parameters of the filtered flight trajectory to a Mamdani-type fuzzy inference system generated using the MATLAB Fuzzy Logic Toolbox [38, 39].
   b. Output produced by the FIS is the inferred possibility of non-conformance in the behavior of the tracked aircraft.

The system diagram for the proposed approach is identical to that shown in Fig. 3, omitting the consideration of environmental context. Fig. 4 shows the fuzzy inference process, with input and output variables replaced by those described in Section 4.1.1.

4.1.1. Fuzzy Inference Process

Firstly, fuzzification of the input variables is as described in Section 3.2.1. The input variables considered in the current application are obtained from kinematic parameters of the filtered flight trajectory. Each of the input variables, with respect to the tracked aircraft, is defined below.

The first variable is the deviation of the estimated position from the planned position (measured in feet, abbreviated *dp*). The second variable is the deviation of the estimated velocity from the planned velocity (measured in feet per second, abbreviated *dv*). The third variable is the deviation of the estimated heading from the planned heading (measured in radians, abbreviated *dh*). Figs. 12 to 14 show the membership functions for the three input variables. The symbols and their corresponding linguistic values for membership functions are shown in Table I (where applicable).

Next, rule evaluation (application of the fuzzy operator in the antecedent, followed by implication from the antecedent to the consequent) is carried out as stated in Sections 3.2.2 and 3.2.3. The rules used in the current application are listed in Table III. They are based on predetermined threshold values for state deviations in the definition of a "conformance region." Fig. 15 shows the membership functions for the output variable (inferred possibility of non-conformance in the behavior of the tracked aircraft, abbreviated *pnc*).

As mentioned in Sections 3.2.4 and 3.2.5, the output fuzzy sets (assigned by the consequents) of each rule are aggregated to form a single output fuzzy set. Defuzzification of this final output fuzzy set yields the output of the fuzzy inference system, which is a single crisp/non-fuzzy number.

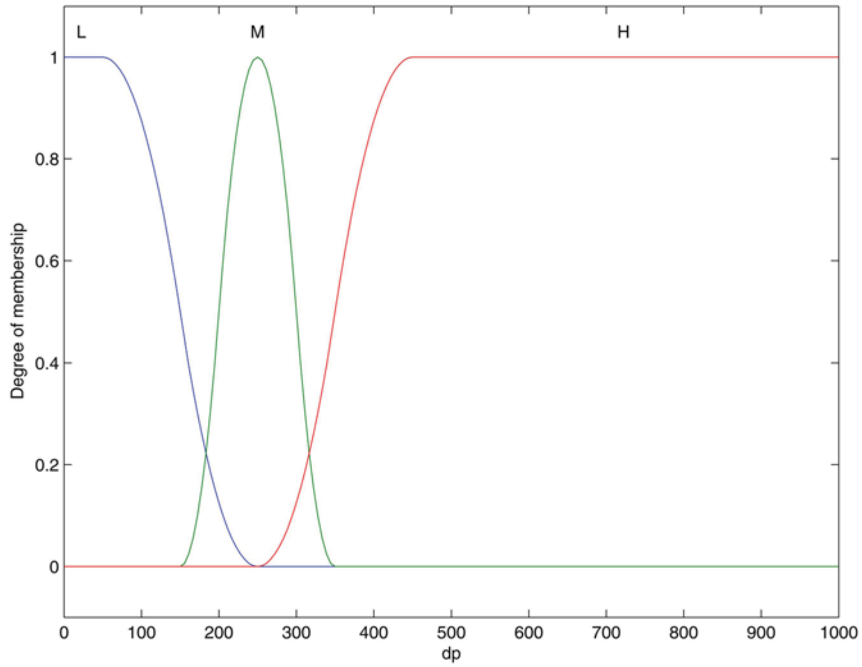

Fig. 12. Membership functions of "dp."

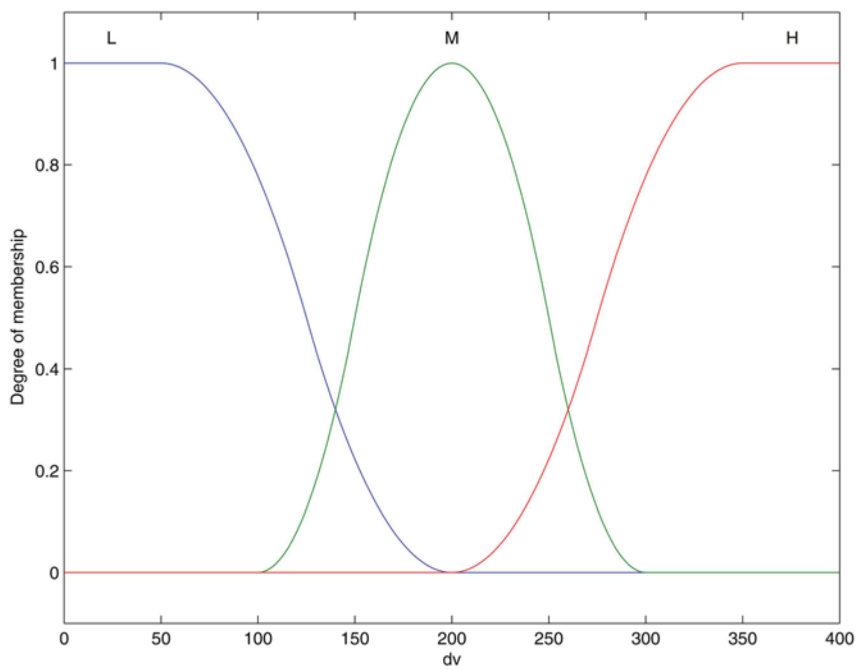

Fig. 13. Membership functions of "dv."

5. SIMULATION TESTS AND RESULTS

We carry out simulation tests to verify the plausibility of the proposed approach. The state estimation component of the method is as follows. Consider a three-dimensional kinetic model described by the discrete-time dynamic system

$$X_{k+1} = f(X_k, w_k) \tag{1}$$

and the measurement/observation equation

$$Z_{k+1} = h(X_{k+1}, v_{k+1}). \tag{2}$$

At time step k, the state vector is $X_k = [x_k, y_k, z_k, \dot{x}_k, \dot{y}_k, \dot{z}_k]^T$. The process noise vector w_k is assumed to be white Gaussian with covariance matrix Q. The measurement vector is Z_k and the measurement noise vector v_k is assumed to be white Gaussian with covariance matrix R. Scalar matrices are used for Q and R. The sampling interval is $T = 1$ (second).

The IMM algorithm used in this section comprises a constant velocity model and two coordinated turn models (one left-turn and one right-turn). The transi-

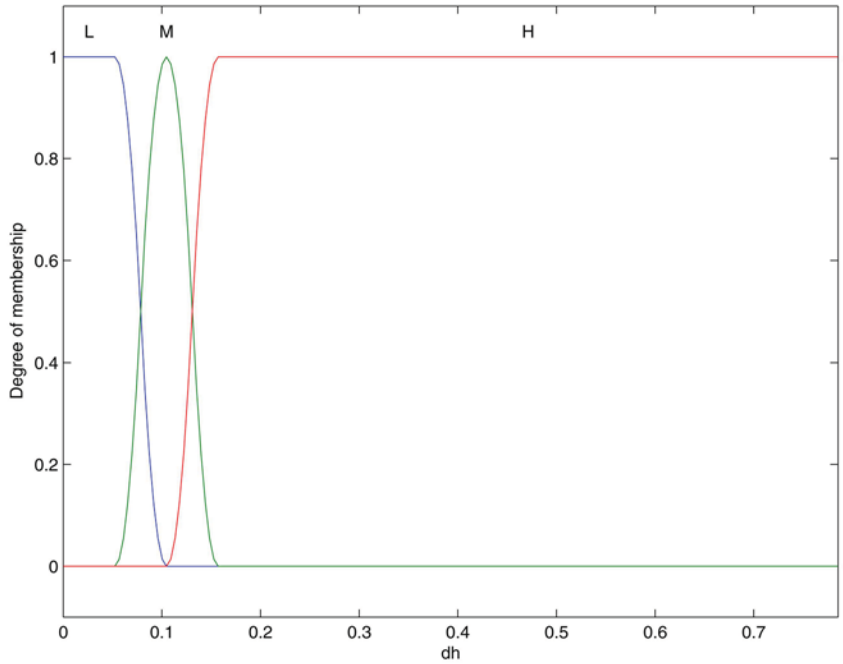

Fig. 14. Membership functions of “dh.”

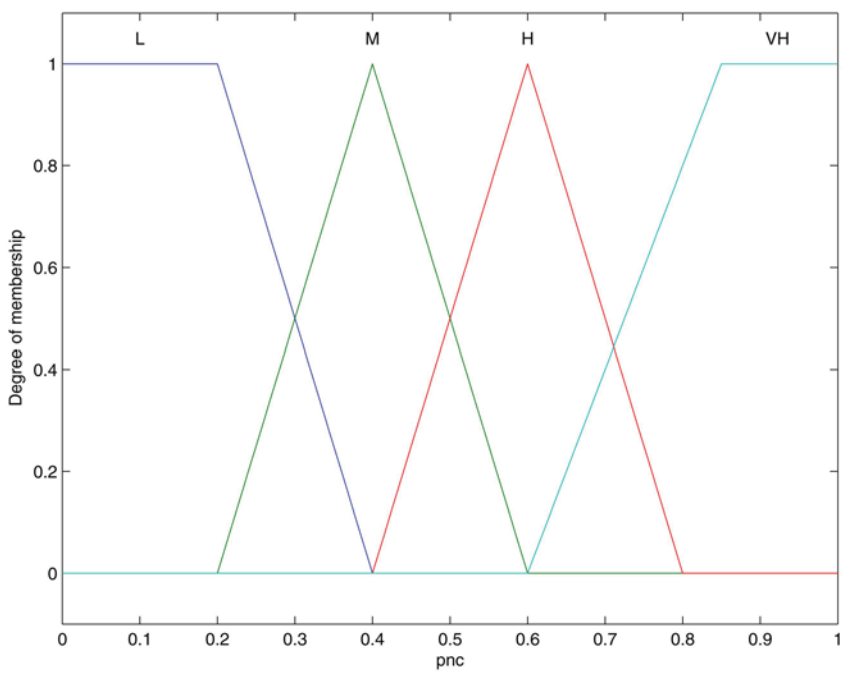

Fig. 15. Membership functions of “pnc.”

tion probability matrix and the initial mode probability are

$$\begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix} \quad \text{and} \quad [0.9 \quad 0.05 \quad 0.05]$$

respectively. The choices made for the transition probability matrix values [2, 29] are based on the following reasons. The frequency of mode switches for a tracked target is expected to be low, compared to that of it staying in the same mode (that is, remaining in the same type of motion). The probability of a switch from the current mode to another is expected to be the same for each of the remaining modes. The expected sojourn time of the system in the constant velocity mode is likely to be higher than in the other modes. In addition, the two coordinated turn models only differ in their turning directions, so the transition probabilities for them are set in the same way.

TABLE III
Rules for Fuzzy Inference System
(Conformance Monitoring)

R1.	(dp is L) & (dv is L) & (dh is L) → (pnc is L)
R2.	(dp is L) & (dv is L) & (dh is M) → (pnc is M)
R3.	(dp is L) & (dv is L) & (dh is H) → (pnc is M)
R4.	(dp is L) & (dv is M) & (dh is L) → (pnc is M)
R5.	(dp is L) & (dv is M) & (dh is M) → (pnc is M)
R6.	(dp is L) & (dv is M) & (dh is H) → (pnc is H)
R7.	(dp is L) & (dv is H) & (dh is L) → (pnc is M)
R8.	(dp is L) & (dv is H) & (dh is M) → (pnc is H)
R9.	(dp is L) & (dv is H) & (dh is H) → (pnc is VH)
R10.	(dp is M) & (dv is L) & (dh is L) → (pnc is M)
R11.	(dp is M) & (dv is L) & (dh is M) → (pnc is M)
R12.	(dp is M) & (dv is L) & (dh is H) → (pnc is H)
R13.	(dp is M) & (dv is M) & (dh is L) → (pnc is M)
R14.	(dp is M) & (dv is M) & (dh is M) → (pnc is H)
R15.	(dp is M) & (dv is M) & (dh is H) → (pnc is VH)
R16.	(dp is M) & (dv is H) & (dh is L) → (pnc is M)
R17.	(dp is M) & (dv is H) & (dh is M) → (pnc is H)
R18.	(dp is M) & (dv is H) & (dh is H) → (pnc is VH)
R19.	(dp is H) & (dv is L) & (dh is L) → (pnc is M)
R20.	(dp is H) & (dv is L) & (dh is M) → (pnc is H)
R21.	(dp is H) & (dv is L) & (dh is H) → (pnc is VH)
R22.	(dp is H) & (dv is M) & (dh is L) → (pnc is M)
R23.	(dp is H) & (dv is M) & (dh is M) → (pnc is H)
R24.	(dp is H) & (dv is M) & (dh is H) → (pnc is VH)
R25.	(dp is H) & (dv is H) & (dh is L) → (pnc is H)
R26.	(dp is H) & (dv is H) & (dh is M) → (pnc is VH)
R27.	(dp is H) & (dv is H) & (dh is H) → (pnc is VH)

5.1. Weapon Delivery by Attack Aircraft

We use the simulation results for the following test examples to evaluate the effectiveness of the proposed method.

EXAMPLE 1. Aircraft in surveillance region of low to high LSI.

We use computation formulas in [40] to determine pop-up delivery parameters. Simulation is carried out on 100 different flight trajectories which are generated using various pop-up delivery parameter values.

For each test, as described in Procedure 1 (see Section 3.2), the IMM algorithm is applied to update the state vectors obtained from each flight trajectory. In the filter used, the discrete-time dynamic system of each model is of the form represented by Equations 1 and 2. Next, for each state estimate, determine the environmental context and the corresponding location sensitivity index.

Let A denote the xy-plane (horizontal plane) portion of the entire surveillance region, with the navigation convention (azimuth = 0 along the positive y-axis). Consider the partition

$$A = \bigcup_{i=1}^{2}\bigcup_{j=1}^{8} A_{ij}$$

where
A_{1j} is the jth octant with $x^2 + y^2 < B_2^2$, $j = 1,\ldots,8$,
A_{2j} is the jth octant with $B_2^2 \le x^2 + y^2 < B_1^2$,

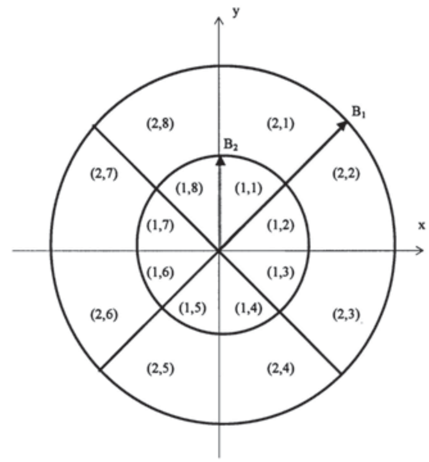

Fig. 16. Partition of surveillance region (xy-plane).

$j = 1,\ldots,8$, and bounds B_1 and B_2 are given positive constants.

The environmental contexts of the partition subsets of A are predetermined and can vary. Let M be a given matrix corresponding to the partition of A, where the LSI for each partition subset A_{ij} is $M(i,j)$, $i = 1,2$, $j = 1,\ldots,8$. Fig. 16 shows the layout for A, with each partition subset denoted according to its subscript by (i,j), $i = 1,2$, $j = 1,\ldots,8$. For each state estimate X_k of the flight trajectory obtained from the filtering process, use the position components x_k and y_k to identify the partition subset, $A_{i(k),j(k)}$, that X_k is in and the corresponding LSI, $M(i(k),j(k))$. The relevant parameters of the flight trajectory obtained from the filtering process and the LSI obtained for the track state estimates are input to a Mamdani-type fuzzy inference system generated using the MATLAB Fuzzy Logic Toolbox [38, 39]. The output produced by the fuzzy inference system is the inferred possibility of the tracked aircraft carrying out a weapon delivery. In this application, we propose to classify a tracked aircraft as having adversarial intent when the fuzzy inference system output exceeds 0.85.

Fig. 17 shows typical results obtained at different phases of the filtered flight trajectory (lower graph), in a scenario where the tracked aircraft travels from regions of low to high sensitivity (and LSI). In the upper graph, the solid curve shows the FIS output values (denoted by P henceforth, in this and subsequent test examples) obtained with only the flight profile considered during simulation. The dash-dot curve shows the FIS output values (denoted by P' henceforth, in this and subsequent test examples) obtained via simulation with both the flight profile and the environmental context of the tracked aircraft considered. Table IV shows P and P' corresponding to the five specific points (defined in Section 3) on the filtered flight trajectory.

It can be observed that P increases as time passes during the tracking process. The surge in P at scan 19 is triggered by motion that is characterized/interpreted by the FIS as the onset of transition from the climb-

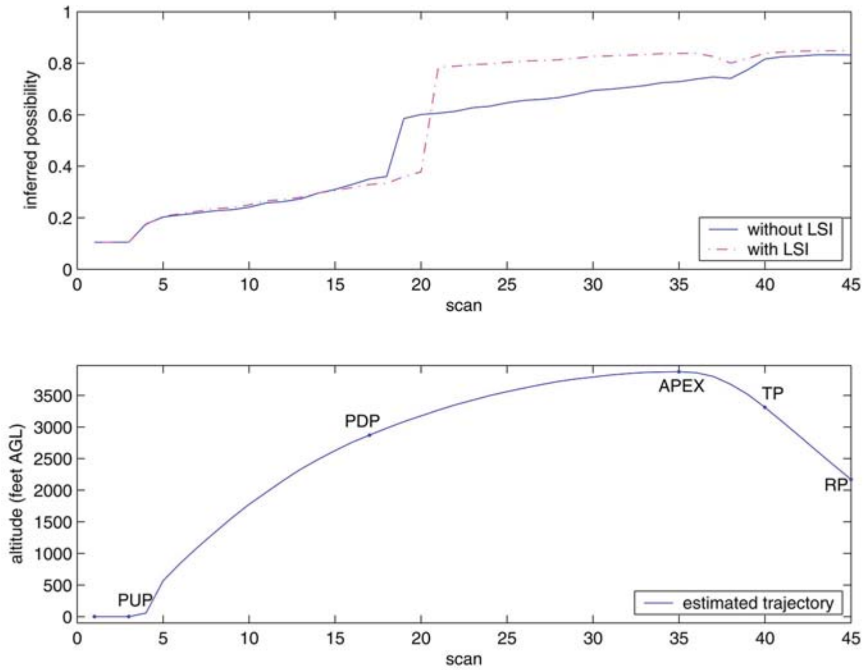

Fig. 17. Example 1—Fuzzy inference system output.

TABLE IV
Example 1—Fuzzy Inference System Output (to 3 decimal places)

Position on Flight Profile	PUP	PDP	Apex	TP	RP
Without LSI	0.105	0.350	0.728	0.816	0.832
With LSI	0.105	0.329	0.838	0.839	0.848

ing to the diving portion of a pop-up delivery. Thus, the FIS returns a significant increase in P, for warning purposes. P attains its peak around (and beyond) the apex. P remains high in the later part of the tracking process. This observation provides verification for the feasibility of our proposed approach for adversarial intent inference, based on the assumption that the aircraft is approaching its weapon release point.

In regions of low (respectively, high) sensitivity, low (respectively, high) corresponding LSI brings about $P' < P$ (respectively, $P' > P$). In the latter situation, the higher P' is likely to be useful in raising military defenders' alert against a potential adversary.

It appears from the simulation results that a tracked aircraft is very likely to carry out a weapon delivery when P (or P') exceeds 0.85. It is probably appropriate for military defenders to raise the level of vigilance when P (or P') exceeds 0.7. This would allow them to have more time to devise and take pre-emptive action against the potential adversary. Fig. 17 shows that P' exceeds 0.7 earlier than P. This provides justification that taking into consideration the environmental context of the tracked aircraft is useful for improving the efficiency of our approach for adversarial intent inference.

EXAMPLE 2. Aircraft in surveillance region of low LSI.

This example is analogous to Example 1, with the entire surveillance region being of low LSI. Typical simulation results obtained are shown in Fig. 18.

The shapes of the plotted curves are similar to the corresponding ones in Fig. 17. During the early stages of tracking, P and P' are low and almost identical. As in Example 1, there is a surge in P at scan 21, which is triggered by motion that is interpreted by the FIS as the onset of transition from climbing to diving portion of a pop-up delivery. Towards the later part of the tracking process, P exceeds 0.7, which is reasonably high. On the other hand, $P' < P$ and remains below 0.6, which is moderate. In addition, P does not exceed 0.75, which is below the proposed threshold value of 0.85 for classifying an aircraft as having adversarial intent.

Compared to Example 1, there appears to be less critical need/urgency in taking action against the tracked aircraft. This is due to the low sensitivity in the surveillance region, which leads to relatively lower P' values when corresponding P values become high. However, it would probably be advisable for the defenders to maintain their vigilance against such an aircraft, whose flight profile closely resembles that of a pop-up delivery.

EXAMPLE 3. Aircraft cruising at high altitude.

We consider an aircraft that cruises at high altitude throughout the approach. Two possible scenarios are described as follows.

EXAMPLE 3a. Aircraft cruising in surveillance region of low to high LSI.

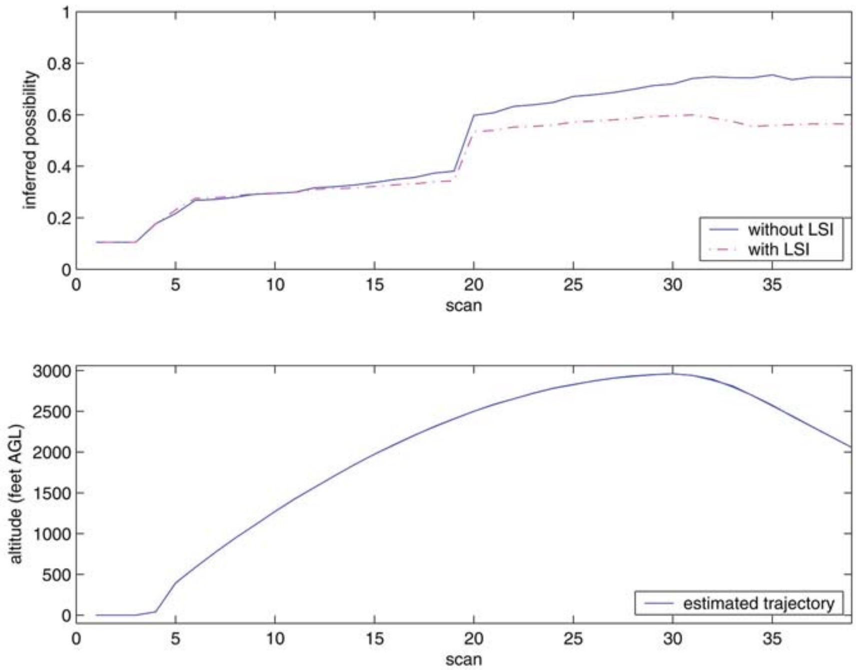

Fig. 18. Example 2—Fuzzy inference system output.

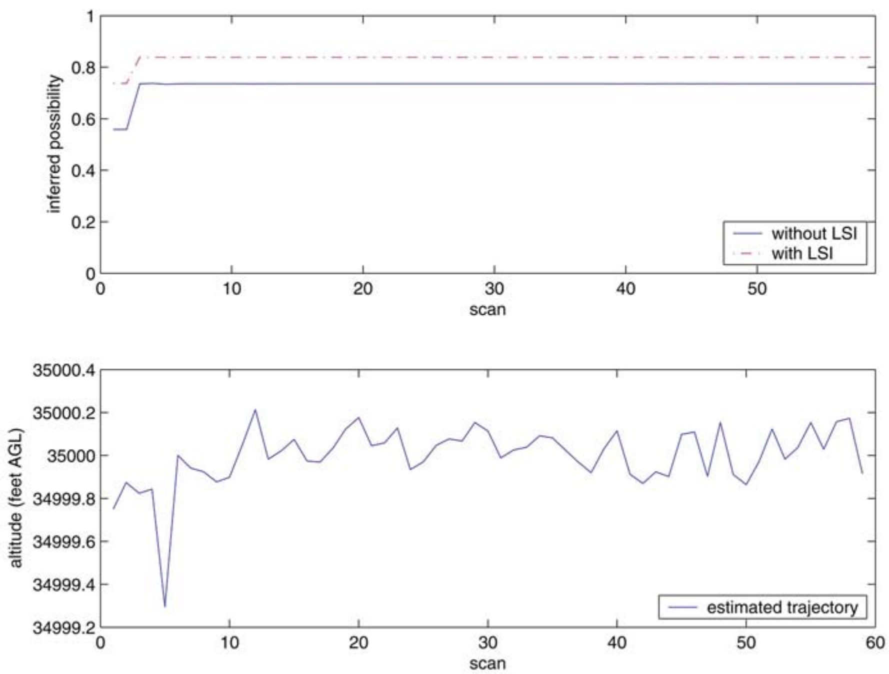

Fig. 19. Example 3a—Fuzzy inference system output.

It can be observed from Fig. 19 that a relatively high value of $P > 0.7$ is reached during tracking. However, there is no further flight motion that indicates an impending attack, which would have caused an increase in P. In this situation, $P' > P$, with $P' \in (0.8, 0.85)$ attained. In view of the high values for P and P', it is very likely for the defenders to be on high alert against possible attack by the aircraft.

EXAMPLE 3b. Aircraft cruising in surveillance region of low LSI.

This example is analogous to Example 3a, with the entire surveillance region being of low LSI. It is apparent from Fig. 20 that the values of P obtained are almost identical to those obtained in Example 3a. Due to the low LSI of the surveillance region, P' remains at a lower level of about 0.5 throughout the approach. It appears from the simulation results that there is no immediate need to raise the defenders' alert against the aircraft.

EXAMPLE 4. Aircraft unlikely to launch an attack.

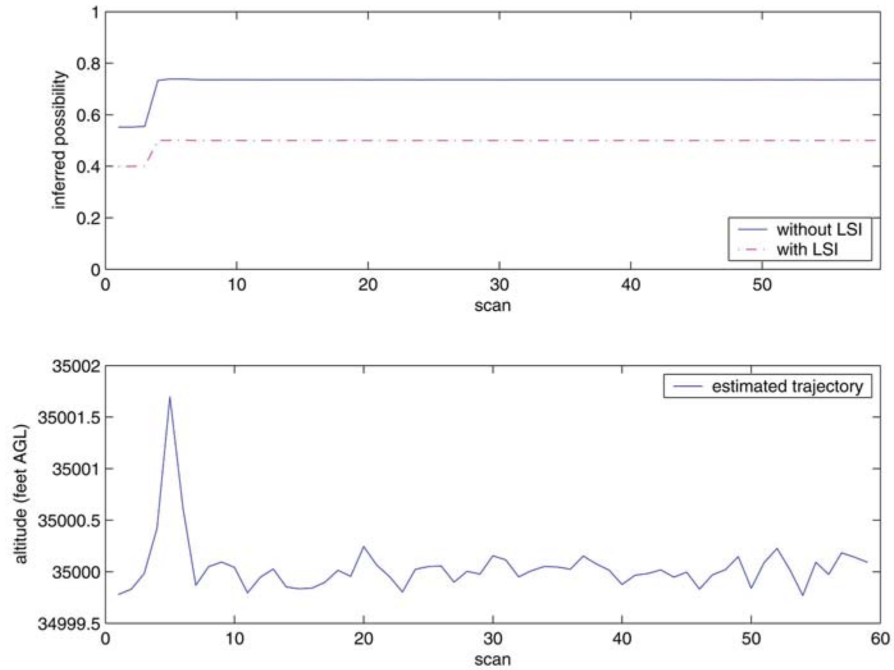

Fig. 20. Example 3b—Fuzzy inference system output.

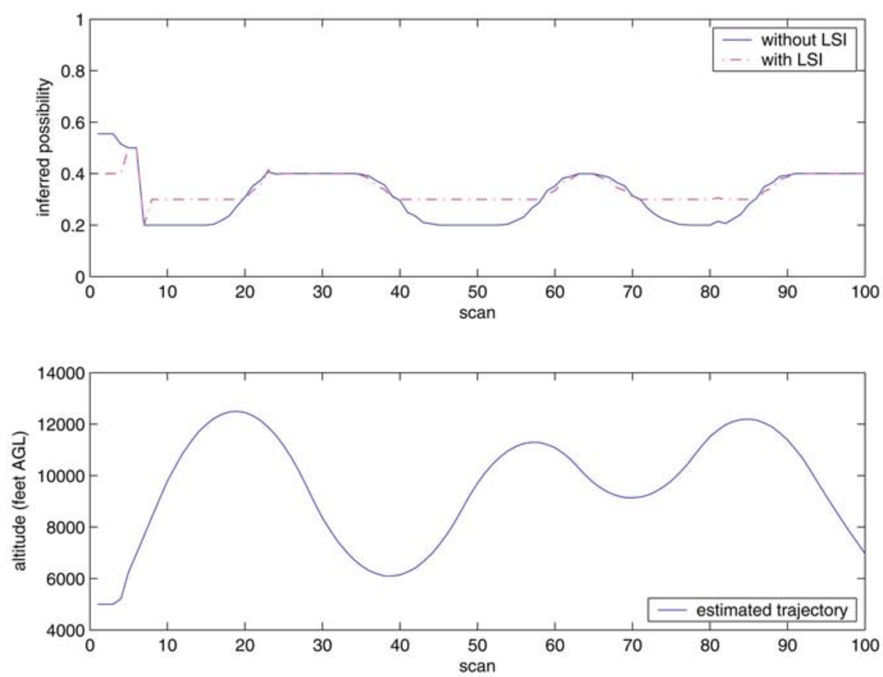

Fig. 21. Example 4—Fuzzy inference system output.

Fig. 21 shows an instance of results obtained for the simulated flight trajectory of an aircraft which is unlikely to carry out a weapon delivery, such as one that is performing aerobatics. It can be seen that P, as well as P', is always below the proposed threshold value of 0.85 for classifying an aircraft as having adversarial intent.

5.2. Conformance Monitoring

Consider the planned flight trajectory shown in Fig. 22. Simulation tests are carried out on 100 flight profiles generated using different combinations of flight parameters (based on existing computation formulas and constraints). For each test, Procedure 2 (see Section 4.1) is carried out to obtain the inferred possibility of non-conformance in the behavior of the tracked aircraft. We categorize aircraft behavior into three types, namely, *conforming*, *non-conforming* and *ambiguous* [31], in our discussion. Fig. 23 depicts typical simulation results obtained.

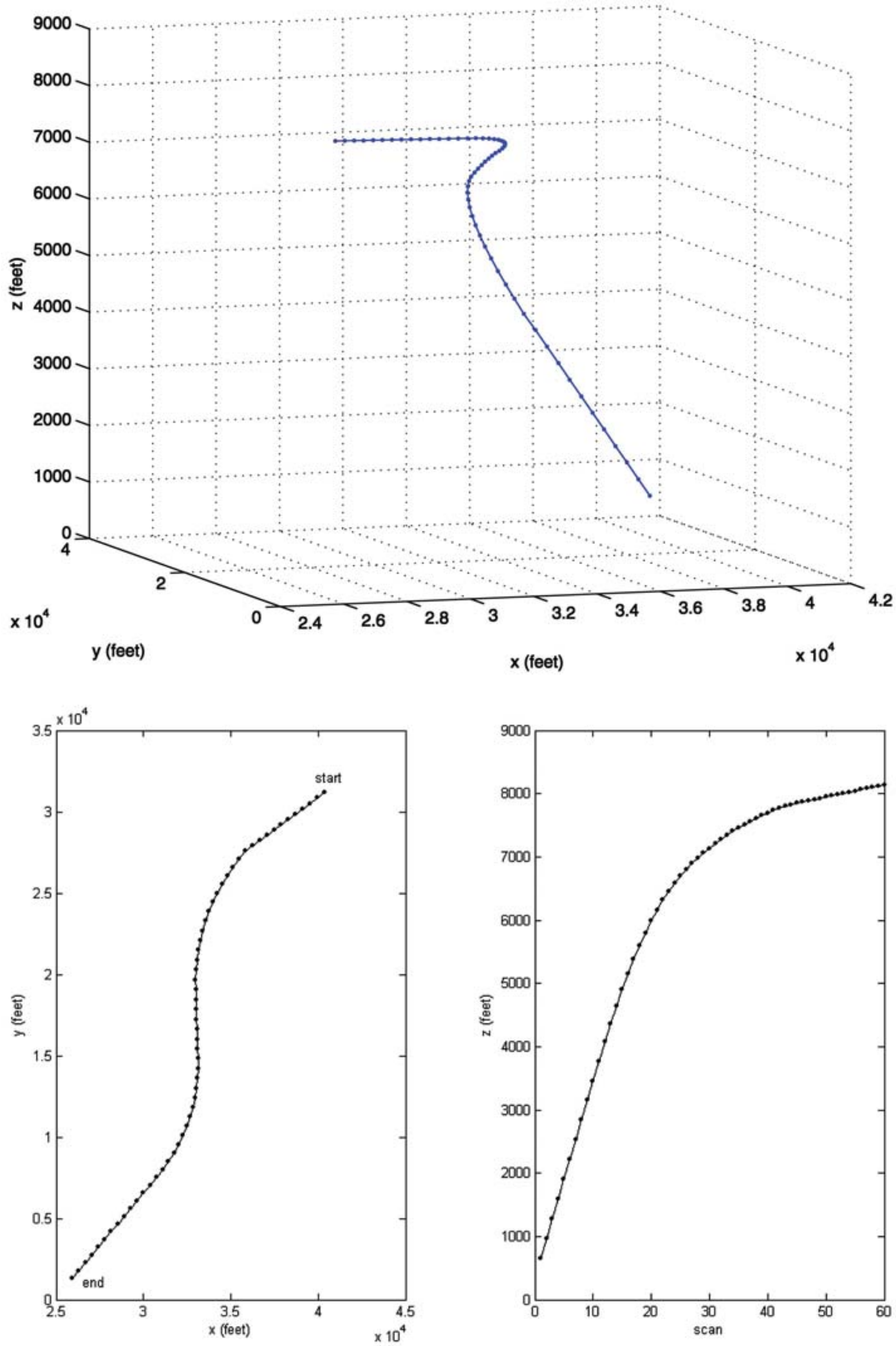

Fig. 22. Planned flight trajectory.

For the conforming case, FIS output values (denoted by P'' henceforth) remain consistently moderate throughout the tracking process. The corresponding deviations from planed states (namely, position, velocity and heading) are relatively small. For the non-conforming case, P'' rises rapidly after an initial period of low to moderate values during tracking. The surge in P'' is due to significant increases in state deviations. The third type of aircraft behavior is considered ambiguous due to indefiniteness in the behavioral traits represented by P''. In this case, there exist instances when P'' increases to become sufficiently large to indicate non-conformance, where corresponding state deviations manifest aberrant behavior in aircraft maneuver. However, P'' subsequently decreases to the extent that conformance is signified, where corresponding state deviations provide evidence of a shift towards the right direction of travel.

It appears from the simulation results that aircraft behavior can be deemed non-conforming when $P'' > 0.85$. It is suggested that alert against non-conformance should be raised when $P'' > 0.7$. This would enable ATC/ATM system controllers to provide the pilot with early warning against navigating beyond safety limits.

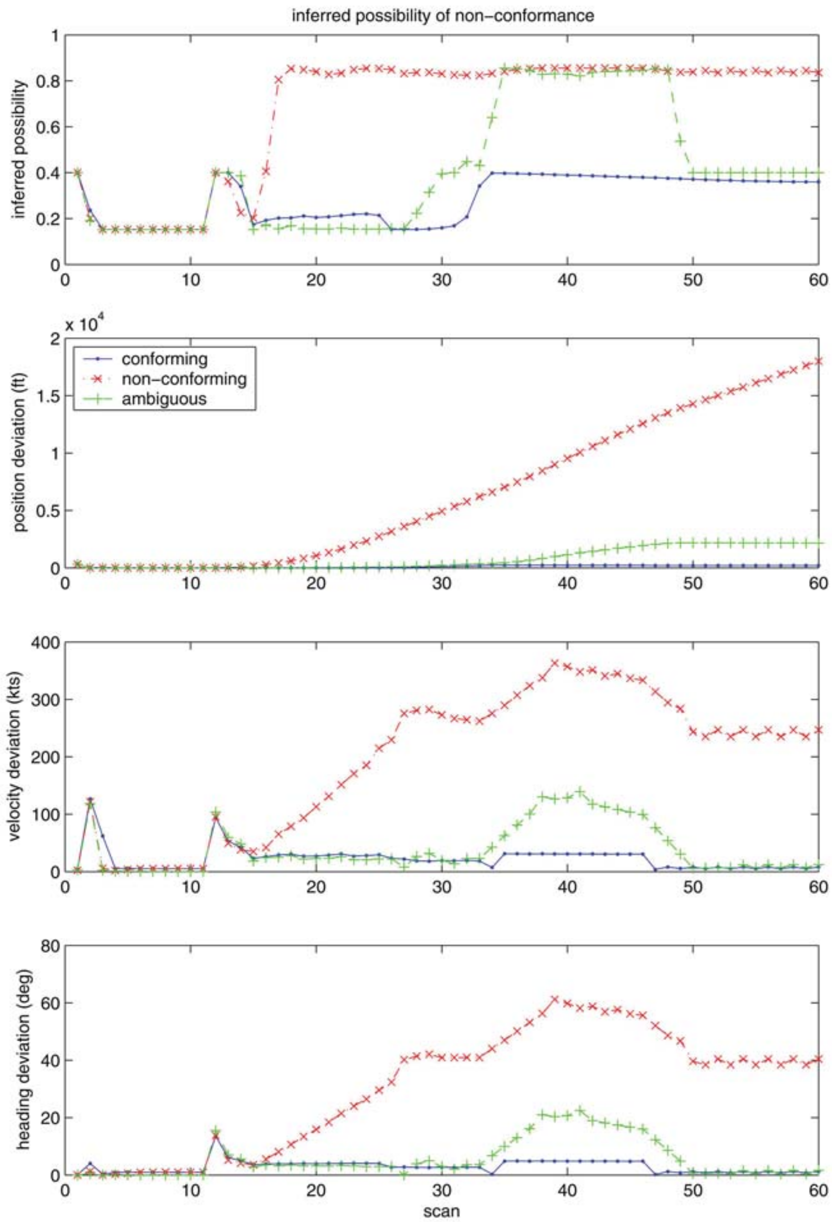

Fig. 23. Fuzzy inference system output (conformance monitoring).

Consequently, the pilot would likely be able to execute necessary maneuvers to steer back towards the planned trajectory with less delay.

6. APPROACH BY MORE THAN ONE AIRCRAFT

Our proposed method deals with intent inference for a single aircraft. The problem on handling an approach by multiple aircraft in military surveillance and air traffic control/management would be more complex and would require much additional consideration. Some issues associated with this problem are discussed below.

6.1. Flight Formation

The flight approach can be in individual form or in a formation. Some examples of flight formations employed by tactical combat aircraft are briefly described in this section [40].

6.1.1. Two-ship Formation

In a line abreast formation, the position of the wingman[2] relative to the flight leader is 0° to 20° aft, 4000 to 12000 feet spacing with altitude separation. A vertical stack of 2000 to 6000 feet is used, when applicable, to minimize the chance of simultaneous detection by an opponent.

For a fighting wing formation, the wingman is given a maneuvering cone from 30° to 70° aft of line abreast and lateral spacing between 500 and 3000 feet. This

[2]Wingman: in a formation of aircraft, the pilot who flies behind and to the side of the leader.

formation is employed when maximum maneuvering potential is desired.

6.1.2. Four-ship Formation

The four-ship formation is employed under the control of one flight leader. It is employed as a single entity as long as it is not forced to separate into a lead element (flight leader and his wingman) and a second/trailing element (second leader and his wingman).

In a box formation, the two-ship elements use basic line abreast maneuvering and principles concerning lookout responsibilities. Depending on terrain and weather, the trailing element takes 1.5 to 3 nautical miles separation from the lead element. The spacing serves the purpose of maximizing separation to avoid easy visual detection of the entire flight formation. maneuvers are initiated by the element leaders in this formation.

For a fluid four formation, the element leaders maintain line abreast formation, while their wingmen assume fighting wing. The flight leader is at the front of the formation, with his wingman to his rear left. The second leader is to the rear right of the flight leader, while his wingman assume fighting wing. The assembly of four of these formations forms a squadron formation.

In a spread four formation, the element leaders maintain the same spacing as for the fluid four formation. The wingmen position themselves 0° to 30° to the rear of their respective element leaders at 6000 to 9000 feet spread. The increase in lateral spacing for wingmen facilitates maneuvering. The elements need not always be line abreast. There may be instances when are briefly in trail. Spread formation makes it difficult to visually acquire the entire flight formation.

A three-ship contingency formation can be considered as an alternative for a four-ship formation mission in some occasions. It is obtained from the four-ship formation concerned by having an appropriate flight member fall out from the original formation.

6.1.3. Echelon Formation

The flight members are arranged diagonally in an echelon formation. Each member is positioned to the rear right, or to the rear left, of the member ahead. These two types of formations are known as a right echelon and a left echelon respectively.

6.2. Multiple Target Tracking and Identity Management

The problem of dealing with approach by more than one aircraft requires the employment of multiple target tracking techniques [4–6, 13, 14, 26, 28] for the state estimation component of our proposed intent inference method. For each tracked aircraft, information based on the estimated kinematic states need to be taken into consideration for processing by a fuzzy inference system, in order to derive the pilot intent.

As mentioned before, the amount of computational load/time is a critical factor for the two intent inference problems discussed here. Hence, it is desirable to select multiple target tracking algorithms with modest time complexities.

Another point of concern is the detection and identification of the targets under surveillance. It may be difficult to distinguish the targets from one another during tracking when there is close proximity and/or interaction among them, such as in the case of a tactical aircraft formation.

To address the aforementioned issues, the multiple-target tracking and identity management (MTIM) algorithm developed in [14] could be considered. The MTIM algorithm is constituted of the following components:

- data association—uses a computationally efficient algorithm based on the joint probabilistic data association algorithm [24], in which measurement data is associated with targets via the use of target kinematic information (position and velocity);
- tracking/hybrid state estimation—uses residual-mean IMM algorithm based on multiple aircraft dynamics models; and
- identity management—uses an algorithm with the ability to keep track of target identities via the use of local attribute information about them (either explicitly available from sensors or inferred from a technique based on the multiple hypothesis tracking algorithm [24]).

The applicability of the MTIM algorithm for incorporation into the intent inference method proposed in this paper could be investigated as part of our future research.

7. SUMMARY

In this paper, we have presented an approach for intent inference, which concerns the use of available knowledge on the preceding activities of a target of interest to predict its future action. The approach is based on the analysis of aircraft flight profiles. The method is implemented for two applications.

Firstly, it has been shown that it is possible to infer the intent of an attack aircraft, particularly on its weapon delivery. The proposed approach is extended to consider the environmental context of the tracked aircraft when executing the inference process. Simulation is carried out on four test examples with different scenarios to evaluate the performance of the method. The results verify the feasibility of the method and its ability to provide timely inference. It is also justifiable to consider the environmental context, which is useful in raising military defenders' level of vigilance early against potential adversaries, hence allowing more time to prepare for pre-emptive action.

In the second application, experimental results show that the proposed solution has much potential in being a useful tool for conformance monitoring in ATC/ATM. It can be used to assist ATC/ATM system controllers in determining whether aircraft are deviating from or adhering to designated courses of travel. As a result, corrective/remedial actions can be taken once deviant behavior is detected.

Our proposed intent inference method has only considered an approach by a single aircraft. We briefly discuss the extension of the proposed method to deal with an approach by multiple aircraft, such as that by a flight formation. Some of the main issues concerned include multiple target tracking and management of the target identities. These topics are of interest in our future research.

APPENDIX. FUZZY LOGIC

Generally, vagueness and imprecision exist in data/information concerning real-world problems. Fuzzy logic [15, 38], an extension of Boolean logic, was developed to deal with uncertainties associated with problems from practical applications.

In *classical set theory*, a set has a crisp (sharp and clear) boundary and it completely includes or excludes an arbitrarily given element. On the other hand, in *fuzzy set theory*, boundaries between sets of values need not be distinctly defined. A fuzzy set expresses the degree to which an element belongs to a set, where an element can have gradual transition in status from "belongs to a set" to "does not belong to a set."

Let X be a space of objects and x be an arbitrary element of X. For a *classical set* C, $C \subseteq X$, define a *characteristic function* $f: X \mapsto \{0,1\}$ by

$$f(x) = \begin{cases} 0, & x \notin C, \\ 1, & x \in C. \end{cases}$$

Then C can be represented by a set of ordered pairs,

$$C' = \{(x, f(x)) \mid x \in X\}. \tag{3}$$

DEFINITION 1 *Fuzzy sets and membership functions.* Let X be a space of objects which are generically denoted by x. A *fuzzy set* F in X is defined as a set of ordered pairs

$$F = \{(x, \mu_F(x)) \mid x \in X\} \tag{4}$$

where $\mu_F : X \mapsto Y$ is known as the *membership function* for F. The membership function maps each element x of the *input space* (or *universe of discourse*) X to a *degree of membership* (also known as *membership value* or *membership grade*) $\mu_F(x)$ in the *output space* (or *membership space*) Y. For each $x \in X$, $\mu_F(x) \in [0,1]$.

REMARK The definition of a fuzzy set is an extension of the definition of a classical set. In Definition 1, if $Y = \{0,1\}$, then F is reduced to a classical set and $\mu_F(\cdot)$ is the characteristic function of F.

Fuzzy logic is a superset of standard Boolean logic. There exist fuzzy logical operations for fuzzy sets that correspond to Boolean logical operations for classical sets. In the case when membership function values are restricted to the set $\{0,1\}$, fuzzy logical operations and Boolean logical operations are equivalent.

DEFINITION 2 *Fuzzy complement.* A *fuzzy complement* operator is a continuous function $N : [0,1] \to [0,1]$ that meets the basic axiomatic requirements:

$$\begin{aligned} &N(0) = 1 \text{ and } N(1) = 0 \quad \text{(boundary)} \\ &N(a) \geq N(b) \text{ if } a \leq b \quad \text{(monotonicity).} \end{aligned} \tag{5}$$

An optional requirement imposes *involution* on a fuzzy complement:

$$N(N(a)) = a \quad \text{(involution)} \tag{6}$$

which guarantees that the double complement of a fuzzy set is still the set itself.

The *complement* of a fuzzy set F is the fuzzy set $\bar{F}$ (or $\neg F$, NOT F), whose membership function is related to that of F by

$$\mu_{\bar{F}}(x) = N(\mu_F(x)) \tag{7}$$

with the fuzzy complement operator commonly defined by $N(a) = 1 - a$.

DEFINITION 3 *T-norm.* A *T-norm* operator is a binary function $T : [0,1] \times [0,1] \to [0,1]$ that satisfies:

$$\begin{aligned} &T(0,0) = 0, \quad T(a,1) = T(1,a) = a \quad \text{(boundary)} \\ &T(a,b) \leq T(c,d) \text{ if } a \leq c \text{ and } b \leq d \quad \text{(monotonicity)} \\ &T(a,b) = T(b,a) \quad \text{(commutativity)} \\ &T(a,T(b,c)) = T(T(a,b),c) \quad \text{(associativity).} \end{aligned} \tag{8}$$

DEFINITION 4 *T-conorm (or S-norm).* A *T-conorm* (or *S-norm*) operator is a binary function $S : [0,1] \times [0,1] \to [0,1]$ satisfying:

$$\begin{aligned} &S(1,1) = 1, \quad S(0,a) = S(a,0) = a \quad \text{(boundary)} \\ &S(a,b) \leq S(c,d) \text{ if } a \leq c \text{ and } b \leq d \quad \text{(monotonicity)} \\ &S(a,b) = S(b,a) \quad \text{(commutativity)} \\ &S(a,S(b,c)) = S(S(a,b),c) \quad \text{(associativity).} \end{aligned} \tag{9}$$

DEFINITION 5 *Fuzzy intersection (conjunction).* The *intersection* of two fuzzy sets F_1 and F_2 is a fuzzy set F, written as $F = F_1 \cap F_2$ or $F = F_1$ AND F_2. F is specified in general by a T-norm operator $T : [0,1] \times [0,1] \to [0,1]$, which aggregates the membership values of F_1 and F_2 as

$$\mu_F(x) = T(\mu_{F_1}(x), \mu_{F_2}(x)). \tag{10}$$

A frequently used T-norm operator is defined by $T(a,b) = \min(a,b)$, the *minimum* of $\{a,b\}$ (also denoted by $a \wedge b$).

DEFINITION 6 *Fuzzy union (disjunction).*
The *union* of two fuzzy sets F_1 and F_2 is a fuzzy set F, written as $F = F_1 \cup F_2$ or $F = F_1$ OR F_2. F is specified in general by a T-conorm (or S-norm) operator $S : [0,1] \times [0,1] \rightarrow [0,1]$, which aggregates the membership values of F_1 and F_2 as

$$\mu_F(x) = S(\mu_{F_1}(x), \mu_{F_2}(x)). \tag{11}$$

A frequently used S-norm operator is defined by $S(a,b) = \max(a,b)$, the *maximum* of $\{a,b\}$ (also denoted by $a \vee b$).

For an input vector $x \in X$, a fuzzy inference process utilizes a set of fuzzy rules to interpret the values of x and assign appropriate values to an output vector $y \in Y$. Each rule is of the form "if S_1 then S_2," or equivalently, "$S_1 \rightarrow S_2$." The if-part of the rule "S_1" is called the *antecedent*, while the then-part of the rule "S_2" is called the *consequent*. Each rule outputs a fuzzy set. Aggregation of the output fuzzy sets for the rules yields a single output fuzzy set. Defuzzification is carried out on the resultant set to obtain the final desired conclusion, in the form of a single number.

REFERENCES

[1] A. Aligawesa and K. L. Fetzer
Intent inference and conformance monitoring in air traffic control.
Project Report, Flight Dynamics and Control/Hybrid Systems Laboratory, School of Aeronautics and Astronautics, Purdue University, Apr. 2008.

[2] Y. Bar-Shalom, X.-R. Li and T. Kirubarajan
Estimation with Applications to Tracking and Navigation: Theory, Algorithms, and Software.
New York: Wiley, 2001.

[3] B. Bell, E. Santos, Jr. and S. M. Brown
Making adversary decision modeling tractable with intent inference and information fusion. In *Proceedings of the 11th Conference on Computer-Generated Forces and Behavior Representation*, Orlando, FL, May 7–9, 2002, 535–542.

[4] H. A. P. Blom and E. A. Bloem
Joint particle filtering of multiple maneuvering targets from unassociated measurements.
Journal of Advances in Information Fusion, **1**, 1 (July 2006), 15–34.

[5] H. A. P. Blom and E. A. Bloem
Bayesian tracking of two possibly unresolved maneuvering targets.
IEEE Transactions on Aerospace and Electronic Systems, **43**, 2 (Apr. 2007), 612–627.

[6] B. Chen and J. K. Tugnait
Tracking of multiple maneuvering targets in clutter using IMM/JPDA filtering and fixed-lag smoothing.
Automatica, **37**, 2 (Feb. 2001), 239–249.

[7] S.-B. Cho
Incorporating soft computing techniques into a probabilistic intrusion detection system.
IEEE Transactions on Systems, Man, and Cybernetics—Part C: Applications and Reviews, **32**, 2 (May 2002), 154–160.

[8] J. P. Coyne
Bombology.
Air Force Magazine, **73**, 6 (June 1990), 64–69.

[9] P. H. Foo, G. W. Ng, K. H. Ng and R. Yang
Application of intent inference for surveillance and conformance monitoring to aid human cognition.
In *Proceedings of the 10th International Conference on Information Fusion*, Québec, Canada, July 9–12, 2007, paper 1309.

[10] J. Franke, S. M. Brown, B. Bell and H. Mendenhall
Enhancing teamwork through team-level intent inference.
In *Proceedings of the International Conference on Artificial Intelligence*, Las Vegas, NV, June 26–29, 2000.

[11] D. L. Hall and S. A. H. McMullen
Mathematical Techniques in Multisensor Data Fusion (2nd ed).
Boston, MA: Artech House, 2004.

[12] L. D. Hudson, B. S. Ware, K. B. Laskey and S. M. Mahoney
An application of Bayesian networks to antiterrorism risk management for military planners.
Technical Report C4I-05-01, Center of Excellence in Command, Control, Communications, Computing and Intelligence (C4I Center), George Mason University, 2001.

[13] C. Hue, J.-P. Le Cadre and P. Pérez
Sequential Monte Carlo methods for multiple target tracking and data fusion.
IEEE Transactions on Signal Processing, **50**, 2 (Feb. 2002), 309–325.

[14] I. Hwang, H. Balakrishnan, K. Roy and C. Tomlin
Multiple-target tracking and identity management algorithm with application to aircraft tracking.
Journal of Guidance, Control and Dynamics, **30**, 3 (May–June 2007), 641–653.

[15] J.-S. R. Jang, C.-T. Sun and E. Mizutani
Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence.
Upper Saddle River, NJ: Prentice-Hall, 1997.

[16] P. Jarvis, T. F. Lunt and K. L. Myers
Identifying terrorist activity with AI plan recognition technology.
In *Proceedings of the 19th National Conference on Artificial Intelligence, 16th Conference on Innovative Applications of Artificial Intelligence*, San Jose, CA, July 25–29, 2004, 858–863.

[17] L. A. Klein
Sensor and Data Fusion: A Tool for Information Assessment and Decision Making.
Bellingham, WA: SPIE Press, 2004.

[18] A. Kott and W. M. McEneaney (eds.)
Adversarial Reasoning: Computational Approaches to Reading the Opponent's Mind.
Boca Raton, FA: Taylor & Francis, 2006.

[19] J. Krozel and D. Andrisani, II
Intent inference with strategic path prediction.
Journal of Guidance, Control, and Dynamics, **29**, 2 (Mar.–Apr. 2006), 225–236.

[20] J. Krozel, T. Mueller and D. Schleicher
Intent inference, confidence assessment, and hazard prioritization status report.
Technical Report TR 99175.30-02, Seagull Technology, Inc., Mar. 2000.

[21] C. G. Looney and L. R. Liang
Cognitive situation and threat assessments of ground battlespaces.
Information Fusion, **4**, 4 (Dec. 2003), 297–308.

[22] E. Mazor, A. Averbuch, Y. Bar-Shalom and J. Dayan
Interacting multiple model methods in target tracking: A survey. *IEEE Transactions on Aerospace Electronic Systems*, **34**, 1 (Jan. 1998), 103–123.

[23] M. Negnevitsky
Artificial Intelligence: A Guide to Intelligent Systems (2nd ed).
Harlow, England and New York: Addison-Wesley, 2005.

[24] G. W. Ng
Intelligent Systems—Fusion, Tracking and Control.
Baldock, Hertfordshire, England: Research Studies Press Ltd. and Philadelphia, PA: Institute of Physics Publishing, 2003.

[25] G. W. Ng, K. H. Ng, R. Yang and P. H. Foo
Intent inference for attack aircraft through fusion. In *Proceedings of SPIE, Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applications 2006*, Orlando, FL, Apr. 19–20, 2006, 6242-06.

[26] S. Oh and S. Sastry
An efficient algorithm for tracking multiple maneuvering targets.
In *Proceedings of the IEEE Conference on Decision and Control, and the European Control Conference*, Seville, Spain, Dec. 12–15, 2005, 4010–4015.

[27] M. T. Plehn
Control warfare: Inside the OODA loop.
Master's thesis, School of Advanced Airpower Studies, Air University, Maxwell Air Force Base, 2000.

[28] S. Puranik and J. K. Tugnait
Tracking of multiple maneuvering targets using multiscan JPDA and IMM filtering. *IEEE Transactions on Aerospace and Electronic Systems*, **43**, 1 (Jan. 2007), 23–35.

[29] K. V. Ramachandra
Kalman Filtering Techniques for Radar Tracking.
New York: Marcel Dekker, 1999.

[30] T. G. Reynolds and R. J. Hansman
Analysis of aircraft separation minima using a surveillance state vector approach. In *Proceedings of the FAA/Eurocontrol International Air Traffic Management R&D Seminar*, Naples, Italy, June 13–16, 2000.

[31] T. G. Reynolds and R. J. Hansman
Conformance monitoring approaches in current and future air traffic control environments.
In *Proceedings of the IEEE/AIAA 21st Digital Avionics Systems Conference*, Irvine, CA, Oct. 27–31, 2002, 2, 7.C.1-1–7.C.1-12.

[32] T. G. Reynolds and R. J. Hansman
Analyzing conformance monitoring in air traffic control using fault detection approaches & operational data.
In *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, Austin, TX, Aug. 11–14, 2003, paper AIAA-2003-5574.

[33] T. G. Reynolds and R. J. Hansman
Investigating conformance monitoring issues in air traffic control using fault detection techniques.
Journal of Aircraft, **42**, 5 (Sept.–Oct. 2005), 1307–1317.

[34] T. G. Reynolds, R. J. Hansman and H. Li
Investigating fundamental issues in lateral conformance monitoring using a fault detection approach.
In *Proceedings of the 5th Eurocontrol/FAA ATM R&D Seminar*, Budapest, Hungary, June 23–27, 2003.

[35] T. G. Reynolds, J. M. Histon, H. J. Davison and R. J. Hansman
Structure, intent & conformance monitoring in ATC.
In *Proceedings of the Workshop on Advanced Technologies and Their Impact on Air Traffic Management in the 21st Century*, Capri, Italy, Sept. 22–26, 2002.

[36] D. D. Salvucci
Inferring driver intent: a case study in lane-change detection.
In *Proceedings of the Human Factors and Ergonomics Society 48th Annual Meeting*, New Orleans, LA, Sept. 20–24, 2004, 2228–2231.

[37] E. Santos, Jr.
A cognitive architecture for adversary intent inferencing: Knowledge structure and computation.
In *Proceedings of SPIE, 17th Annual International Symposium on Aerospace/Defense Sensing and Controls*, Orlando, FL, Apr. 21–25, 2003, 5091, 182–193.

[38] The MathWorks, Inc.
Fuzzy Logic Toolbox User's Guide Version 2, 2002.

[39] The MathWorks, Inc.
Fuzzy Logic Toolbox Version 2.1.2 (Release 13), 2002.

[40] United States Air Force Air Combat Command
Multi-Command Handbook 11-F16 Vol. 5, May 1996.

[41] J. L. Yepes, I. Hwang and M. Rotea
New algorithms for aircraft intent inference and trajectory prediction.
Journal of Guidance, Control, and Dynamics, **30**, 2 (Mar.–Apr. 2007), 370–382.

[42] Y. Zhao, C. Haissig and M. J. Hoffman
Analysis of pilot intent parameters in air traffic management.
In *Proceedings of the American Control Conference*, Philadelphia, PA, June 24–26, 1998, 3, 1789–1792.

Pek Hui Foo received her B.Sc. (Hons.), M.Sc. and Ph.D. degrees from the National University of Singapore in 1999, 2001, and 2009, respectively.

She is currently a Senior Member of Technical Staff at DSO National Laboratories. Her research is on applications of data and information fusion.

Gee Wah Ng received his M.Sc. and Ph.D. from University of Manchester Institute of Science and Technology, United Kingdom.

He is currently a Principal Member of Technical Staff and Programme Director (Information Exploitation) of Information Division at DSO National Laboratories. He has delivered many projects in the decision support areas and has authored two books. He is active in international conferences in the areas of information fusion and intelligent systems. His research interests in data and information fusion include target tracking, computational intelligence, machine learning, self-tuning and sensor networks.

Khin Hua Ng received his B.Sc. degree (with 1st class honours) in computational science and mathematics from the National University of Singapore in 1998, and his M.Sc. degree (with distinction) in advanced computing from Imperial College London in 2004.

He is currently a Senior Member of Technical Staff at DSO National Laboratories. His research interests include sensor management, target recognition, intent inference, probabilistic reasoning, and cognitive system.

Rong Yang received her B.E. degree in information and control from Xi'an Jiao Tong University China in 1986, and M.Sc. degree in electrical engineering from the National University of Singapore in 2000.

She is currently a Senior Member of Technical Staff at DSO National Laboratories. Her research interests include target tracking and data fusion.