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LEARNING ATTRIBUTES for SITUATIONAL AWARENESS in the LANDING of an AUTONOMOUS AIRPLANE

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Abstract: The paper investigates situational learning, which utilizes mathematics of probability and evidential theory, to determine the perceivable importance of environmental cues as they contribute to situational awareness. The situation-awareness agent's goal is consistent with that of an aircraft pilot; namely, to land a plane under a variety of weather and runway conditions. Landing requires hypothesis selection which can be formulated as a situational-learning (SL) problem in which sensed states are represented as current situational beliefs. The objective of SL is to learn how to select the optimal set of mutually non-exclusive hypothesis in order to maximize the identification of the situation.

Three methodologies for the combination of sensor measurements for situational learning are designed and analyzed for a system equipped with a position measuring device and identification sensors. Using a learning algorithm for searching, the *a priori* identification probabilities of recognition are known.[1] The methods are 1) recursive **Bayesian** where the probability of the current state is based on the *a priori* information multiplied by the likelihood function, 2) **Dempster-Shafer(DS)** which uses evidential reasoning /accrual to combine information of uncertainty, and 3) **Modified Dempster-Shafer(MDS)** which uses a combination of evidential reasoning and probability analysis. The methods are assessed for cases ***with*** and ***without*** **feedback**.[2] Over time, the evidence/probability accumulates for decision making and a learned decision is made when the belief/probability value is greater than a threshold. Simulations are conducted using a combination of *a priori* probabilities as derived from a learning-search algorithm and measurements from an IRAL (Identification of wind direction from Right, Ahead, and Left; relative to the landing configuration of the plane), an ESM (Electronic Support Measurement), and an IRST(InfraRed Search and Track) sensor for the identification and situational assessment of a runway. (Figure 1) The simulation runs are completed for 100 measurements over a 1*nm* measurement updates. All of the methodologies correctly identified the situation with the ***Modified Dempster-Shafer with feedback*** demonstrating the most efficient solution and shows promise for multisensor data integration for docking or landing purposes for autonomous mobile robots and avionics systems of UAVs.

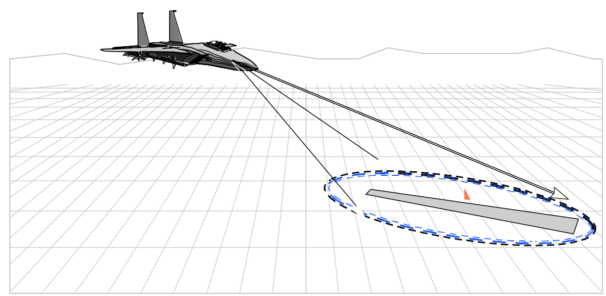

Figure 1. Plane Identifying a Runway for Landing.

1.0 INTRODUCTION

Advancing sensing capabilities are profoundly impacting aeronautical warfare. Offensive sensors such as Radar(SAR, FLIR), along with navigation sensors (GPS, INS) and defensive sensors (ESM, RWR, IRST) are enabling beyond-visual range engagements and providing most of the impetus for avionics improvements.[3] Despite these advanced sensing capabilities, improvements have focused on lower-level issues of information processing such as estimating an object's kinematics, (Kalman Filtering), and identifying objects, (template matching), but do not help to answer the higher-level question: "What is the situation?" Currently, the human operator must integrate the lower-level avionics sensor information to assess the situation and with an increase in 1) number of on-board sensors, 2) reception of off-board information, and 3) increased aircraft responsibilities in swift combat operations, the appeal of automating the "situation awareness process" is rapidly growing [4]

The automation of situational assessment starts with probability theory, but which one? **1) empirical probability** values are derived from "long-run" interpretations of *sampling* distributions which are assigned ***a posteriori***; **2) classical probabilities** are defined by the *potential* for the event of interest to occur as compared to other equally probable outcomes and can be assigned ***a priori***; and **3**) **subjective probabilities** are assigned on the basis of an *experien*ce, of interpreting the available information. Although there is a body of formal mathematical literature on experimental classical and empirical probability, situation awareness still derives

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specific values from individual, personal judgment. For military or defense applications, the appropriate probability often will be of a subjective type because frequently it is the only way that the learned occurrences of so-called singular or rare events can be probabilistically estimated. Thus, the paper shows potentially real-time complement for the human-learned subjective reasoning specific to the situation. The report develops the methodology and presents simulated results for the three methodologies.

2.0 PROBLEM FORMULATION

2.1 Landing A Plane (Semi Autonomous)

One of the many challenges facing a fully autonomous aircraft is an autonomous landing. When the situation is correctly identified, a pilot chooses a specific set of procedures in which to land the plane. The first thing the pilot gets is the wind conditions which can be audio, electronic, or scanning for a wind sock - which is a measurement update to the ILAR sensor. Suffice to say, that the aileron and flaps controls are dependent on winds {crosswind vs. normal}, length of runway {short vs. long}, and surface conditions {soft vs hard}. Pilots also need current weather(nature) and runway(class) type information from offboard ATIS reports and airport directries, respectively; which is an identification update to the ESM and IRST sensors.

2.2 Situational Learning

To learn the situation, three methods are used. a: 1) ***recursive probabilistic approach*** *(Bayes)* 2) ***recursive belief function*** *(DS)* approach (without and with feedback), and 3) ***recursive modified belief function*** *(MDS)* approach (without and with feedback) to identify the type, nature, and class of the target runway, given measured data. A comparison is made to discuss the usefulness of the probability, belief, and modified belief functions for situational leaning.

2.3 Scenario

The scenario is an aircraft identifying a target(runway) using multi-sensor integration to determine which control actions to use in landing. There are three kinds of sensors: an IRAL, ESM, and IRST. Each sensor returns two elements: 1) a belief value (or probability value for the Bayesian approach) and 2) a ten bit measurement vector that represents the proposition to which the belief (or probability is attached). There are ten (10) types of landing situations that can be grouped into four runway classes: {soft, short, long, commercial}, and three natures: four bits {left wind}, five bits {right winds}, and one bit {ahead-on winds}. If a bit is set to 0, this reflects that the sensor declares that the runway in question is not of the type associated with that bit, and if the bit is 1, the runway may be of that type.

In the project, I simulate a landing of an aircraft 100 nautical miles (nm) out and approaches the runway. The measurements are taken every 1 nm and with the assumed uncertainties which are approximately proportional to the distance between the aircraft and the runway. The performance confidence(*a priori* sensor characteristic probability) is shown in Table 1. Each sensor is provided with an array of data. The data set includes the {{range (*nm*)}, {10 measurement bits}, {sensor performance confidence value}}. Two sets of data (for a heavy and light aircraft) are analyzed for the different methodologies.

TABLE 1: Sensor Characteristics

		T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
	prior	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Left Wind	$P(LW \mid T_k)$	0.80	0.80	0.80	0.80	0.10	0.10	0.10	0.10	0.10	0.10
Right Wind	$P(RW \mid T_k)$	0.10	0.10	0.10	0.10	0.80	0.80	0.80	0.80	0.80	0.10
Ahead	$P(A \mid T_k)$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.80
Soft Field	$P(So \mid T_k)$	0.60	0.15	0.15	0.15	0.60	0.60	0.15	0.15	0.15	0.10
Short Field	$P(SF \mid T_k)$	0.15	0.60	0.15	0.60	0.15	0.15	0.60	0.15	0.15	0.10
Long Field	$P(LF \mid T_k)$	0.15	0.15	0.60	0.15	0.15	0.15	0.60	0.15	0.60	0.10
Commercial	$P(CO \mid T_k)$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.70

3.0 THEORETICAL BACKGROUND

3.1 Bayesian Probability Analysis

From the notations of probability mathematics; the joint, marginal, and conditional probabilities can be combined to form the mutually exclusive properties of **Bayes' Rule:**

$$P(B_j \mid A_i) = \frac{P(A_i \mid B_j) \bullet P(B_j)}{\sum_{i=1}^{N} P(A_i \mid B_j) \bullet P(B_j)} \tag{1}$$

where $P(A_i|B_j)$ is the likelihood function, and $P(B_j)$ is the update from the *a priori* information. From Bayes' Rule, these **axioms** hold:

$$\begin{aligned} &P(\phi) = 0 \\ &P(A_i) = 1 - P(A_i) \\ &P(A_i \cup B_j) = P(A_i) + P(B_j) - P(A_i B_j) \\ &P(A_i) = P(A_i|B_j) \bullet P(B_j) + P(A_i|B_j) \bullet P(B_j) \end{aligned} \tag{2}$$

To update the uncertainty based on the new evidence, Bayes' Rule is formulated as:

$$P(C \mid A_i\, B_j) = \frac{P(B_j\, C \mid A_i)}{P(B_j \mid A_i)} \tag{3}$$

If C is an element of a mutually exclusive and collectively exhaustive set of potential outcomes, and B is a set of data that has been collected, then:

$$P(C_k \mid A_i\, B_j) = \frac{P(B_j\, C_k \mid A_i)}{\sum_{k=1}^{N} P(B_j \mid C_k\, A_i) \bullet P(C_k \mid A_i)} \tag{4}$$

from which it can be rewritten as:

$$\boxed{P(C_k \mid A_i\, B_j) = \frac{P(B_j \mid C_k\, A_i) \bullet P(C_k \mid A_i)}{\sum_{k=1}^{N} P(B_j \mid C_k\, A_i) \bullet P(C_k \mid A_i)}} \tag{5}$$

where:

1. $\mathbf{P(C_k|A_i)}$ is an ***a priori*** (or prior) probability of C_k occurring, based on the state of information A_i;
2. $\mathbf{P(C_k|A_i \cdot B_j)}$ is the ***a posteriori*** (or posterior) probability of C_k given the data B_j is observed and prior state information A_i;
3. $\mathbf{P(B_j|C_k \cdot A_i)}$ is the **likelihood function**, likelihood of observing data B_j conditioned on C_k and prior information state A_i;
4. $\sum_{k=1}^{N} \mathbf{P(B_j \mid C_k\, A_i) \bullet P(C_k \mid A_i)}$ is the **preposterior** or probability of the observing the occurring data, given the prior state information, but conditioned on all possible outcomes C_k.

It is possible to aggregate the probability statements from a lower level of abstraction to a higher one using the equations above, and the development can be derived for continuous as well as discrete events, and scalar and vector and matrix notations. The likelihood expressions represent how confident or lack of confidence (subject to change) a given probability statement is. The functions must be developed prior to collecting the data by analysis. Note that the *preposterior* is simply the combination of all the likelihood functions and the prior distributions.

3.2. Bayesian Probability Analysis of IRAL Sensor

The Bayesian method is based upon the basic probability axioms. The first step in the Bayesian approach is to determine, for each sensor, its likelihood function based upon runway situation type. Thus, for the IRAL sensor, the relationship is:

$$P_{IRAL}\,(D|T_k) = \sum_{i=1}^{n} P_{IRAL}\,(D|N_i) \bullet P(N_i|T_k) \tag{6}$$

where N_i is Nature_i (R - right, L - Left, A - Ahead), D is Data, and T is the type. $P_{IRAL}(D|N_i)$ must be determined from the data measured and the *prior* probabilities learned through experience and found in Table 1. The combination of theses values is shown by the relationship:

$$P_{IRAL}(D|L)+P_{IRAL}(D|R)+ P_{IRAL}(D|A) = P_{IRAL} = 1 \tag{7}$$

The data given is in the form of binary values for detection form a single sensor, such as : {{ 1, 1, 1, 1, 0, 0, 0, 0, 1}, {0.7}} which is in the form {{Pr(Detect L), Pr(Detect R), Pr(Detect A)},{Pr(Prior)}}. Taking into account the confidence of the data, whose bits have been set to one, yields the following equations which determine the required probabilities:

$$P_{IRAL}(D|L) = [1+Pr(Prior)] \bullet Pr(Detect\ N_i) \bullet P_{IRAL} \tag{8}$$

So, $P_{IRAL}(D|L) = P_{IRAL}(D|A) = 0.3859$, $P_{IRAL}(D|R) = 0.227$.

The above analysis satisfies the condition that if the confidence of the data is zero, then the maximum uncertainty is achieved as well as the entropy. For the above data, if the confidence is zero, each probability would then equal 0.3333, which satisfies the condition of maximum entropy.

3.3.1 Bayesian Probability Analysis of ESM Sensor

Following the same procedure, the ESM sensor (over its set) gives:

$$P_{ESM}\,(D|T_k) = P_{ESM}(D|T_1) \bullet P(T_1|T_k) + ..\ + P_{ESM}(D|T_N) \bullet P(T_N|T_k) \tag{9}$$

and the relationship below holds:

$$P(T_i|T_k) = \begin{cases} 1 & \text{for } i = k \\ 0 & \text{for } i \neq k \end{cases} \tag{10}$$

So the probability of the type data can be simplified for the ESM sensor, just equal to the measured data itself. The interpretation of the data for the ESM sensor is similar to that the IRAL sensor. For example, if the ESM sensor returns the data string: {{1, 1, 0, 0, 0, 1, 1, 1, 0, 0}},{0.3}} of the form {{$P(T_{1-10})$}, P(Prior)}; then the probabilities would be determined as follows:

$$\sum_{i=1}^{N} P_{ESM}(D|T_i) = P_{ESM} = 1 \tag{11}$$

$$1 = \sum_{i=1}^{N} [(\, 1 + Pr(Prior) \bullet Pr(Detect\ T_i))] \bullet \frac{1}{P_{ESM}} \tag{12}$$

So with the data given $P_{ESM}(D|T_{(1,2,6,7,8)}) = 0.104$
$P_{ESM}(D|T_{(3,4,5,9,10)}) = 0.08$

3.2. Bayesian Probability Analysis of IRST Sensor

The IRST is interpreted the same as the ESM sensor.

3.3 Bayesian Probability Analysis: Integrated Sensors

The sensor data integration is completed by the Bayesian update of information. Since the above information is assumed available, then these ***independent*** likelihood functions can be integrated together to get the joint likelihood function based upon runway situation. The integration of the data is completed as:

$$P_{Int}(D|T_k) = P_{IRAL}(D|T_k) \bullet P_{ESM}(D|T_k) \bullet P_{IRST}(D|T_k) \tag{13}$$

but, the information desired is the likelihood of runway type, given the data; instead of, likelihood of data given the type. Using Bayes' Rule, the relationship is:

$$P_{Integrated}(T_k|D) = \frac{P_{Integrated}(D|T_k) \bullet P_{Prior}(T_k)}{P(D)} \tag{14}$$

where the normalizing factor is:

$$P(\text{Data}) = \sum_{i=1}^{N} P_{\text{Integrated}}(\text{Data}|T_k) \bullet P_{\text{Prior}}(T_k) \tag{15}$$

To determine the runway class and nature, the axioms of probability are used, where the joint likelihood function and the prior information are used to obtain the data:

Wind Nature: {Left, Right, Ahead}

$$P(N_i|D) = \sum_{i=1}^{N} P_{\text{Integrated}}(T_k|D) \bullet P(N_i|T_k) \tag{16}$$

$$P(L|T_k) + P(R|T_k) + P(A|T_k) = 1 \tag{17}$$

Runway Class: {Soft, Short, Long, and Commercial}

$$P(C_i|D) = \sum_{i=1}^{N} P_{\text{Integrated}}(T_k|D) \bullet P(C_i|T_k) \tag{18}$$

$$P(So|T_k) + P(Sh|T_k) + P(L|T_k) + P(C|T_k) = 1 \tag{19}$$

A concern in using Bayes' Rule is the need for *a prior* distribution over the events of interest. In the real world, this necessitates a subjective interpretation of probability or by arbitrarily setting the probabilities for each outcome equal, called the ***principle of indifference***. The Bayesian approach to sensor integration interprets the confidence information at each measurement and its disadvantage is that uncertainty information is not dealt with.

3.4 Dempster-Shafer Evidential Reasoning

The method evidential reasoning is focused on (un)certainty. The combination of the data is based on belief functions, similar to that of Bayes probability functions. Dempster created the belief function and his student, Shafer, used it for evidential reasoning. [5]

To start the analysis, Θ is a Frame of Discernment, which is a finite set of single hypothesis about a problem. A power set 2^{Θ}, is the set of all subsets of Θ. Note, if Θ has *N* elements, then the power set has 2^{N-1} elements. From the power set, uncertainties (upper - support) and (lower - plausibility) are used to analyze the results. **Belief** measures are metrics of uncertainty declarations within evidence theory. When two opinions are pooled, a belief measure is formed and result in the upper and lower measures of uncertainty. The Shafer belief functions are:

1. $b(\phi) = 0$, belief in the impossible is zero
2. $b(\theta) = 1$, the belief in the universal event is unity
3. For every positive integer n and every collection of subsets of Θ $\{A_1, \ldots, A_N\}$

$$b(\cup A_N) \geq \sum_i bA_i - \sum_{i<j} bA_iA_j + \ldots + (-1)^{n+1} b(A_1 \ldots A_N)$$

where $\cup A_N$ is the union of A_1 through A_N

Although the first two are similar to probability analysis, the last deals with sets that are not mutually exclusive. Note that the fourth Bayes' probability axiom, conditional probability, does not have a counterpart conditional belief. Evidence theory possesses the ability to assign an uncommitted belief to the entire frame of discernment (or, assigning belief to a level of admitted ignorance regarding the meaning of evidence).

$$\text{Bel}(A) + \text{Bel}(\bar{A}) \leq 1 \tag{20}$$

where $\text{Bel}(\bar{A})$ is the belief in not A.

Dempster's rule is used to combine probabilistically, independent sets of evidence. Two independent belief functions Bel_1 and Bel_2 existing over a common frame discernment, Θ, is divided into different subsets $\{A_N\}$ and $\{B_M\}$ for each of the two belief functions. Dempster's rule of combination;

$$\text{Bel}(A_i\, B_j) = \frac{\text{Bel}_1(A_i)\, \text{Bel}_2(B_j)}{1 - Q} \tag{21}$$

where $Q = \sum_i \sum_i \text{Bel}_1(A_i)\, \text{Bel}_2(B_j)$ such that $A_iB_i = \phi$.

In effect, Q accounts for **conflicts** in the belief distributions from the sources Bel_1 and Bel_2 and assures that the combined belief is normalized to the unit interval. Note, that the formulation of Dempster's rule is also valid when $\{A_N\}$ and $\{B_M\}$ are identical. When there is no uncommitted belief (ignorance) in either belief function, Dempster's rule is identical to the Bayesian rule. The two rules are also identical when the frames of discernment for the belief functions being operated upon contain the same hypothesis and their conjunctions:

$$\{A_N\} = \{B_M\} = \{A, (\bar{A})\}$$

For the sensor that computes the belief measures Bel_K for *K* elements of the power set and an uncommitted (**ignorant**) belief Ign_U, the following equation represents the belief for each *element k* at the time *n* resulting from applications of Dempster's Rule:

$$\text{Bel}_k(n) = \begin{cases} \text{Bel}_k & \textit{if } n=1 \\ \dfrac{\text{Bel}_k\left[(\text{Bel}_k + \text{Ign}_u)^{n-1} + \sum_{j=1}^{n-1} \text{Ign}_u^j\right]}{\sum_{k=1}^{K} \left\{\text{Bel}_k \bullet \left[(\text{Bel}_k + \text{Ign}_u)^{n-1} + \sum_{j=1}^{n-1} \text{Ign}_u^j\right]\right\} + \text{Ign}_u^n} & \textit{if } n>1 \end{cases} \tag{22}$$

The denominator, for $n > 1$, normalizes the belief assigned to all elements of the power set to sum to 1. Note that the ignorance function at time *n* is a simple function of the number of sensor reports. Using the Equation above, the belief can be calculated over several observational cycles and included in an observational direct *acyclic* graph.

Dillard [6] develops combination rules for multiple sensor integration cycles that are similar to the single sensor cumulative (*n*- observations) **belief** function. The generalization to the case of *i* multiple sensors is:

$$\mathrm{Bel}_k(n) = \frac{\sum^{n}_{K_1 K_1 \ldots K_N = K}\left[\mathrm{Bel}_1(n) \bullet \mathrm{Bel}_2(n) \bullet \ldots \bullet \mathrm{Bel}_j(n)\right]}{1 - Q} \qquad (23)$$

given the *n*th observation and the multisensor (joint or integrated) belief in proposition or object-class *k* in the frame of discernment, Θ. For the **ignorance** function:

$$\mathrm{Bel}_k(n) = \frac{\prod^{i}_{j=1}\ {}_{j_1 j_1 \ldots j_N = J}\left[\mathrm{Ign}_1(n) \bullet \mathrm{Ign}_2(n) \bullet \ldots \bullet \mathrm{Ign}_j(n)\right]}{1 - Q} \qquad (24)$$

where $Q = \sum^{n}_{K_1 K_2 \ldots K_N = K}\left[\mathrm{Bel}_1(n) \bullet \mathrm{Bel}_2(n) \bullet \ldots \bullet \mathrm{Bel}_j(n)\right]$ is the belief attributed to conflicting declarations and used in normalizing the Equations. The cumulative belief across all sensors through time period *n* for proposition of target T_k is given as:

$$\mathrm{Bel}_k(n) = \begin{cases} \mathrm{Bel}_k(1) & \text{if } n = 1 \\ \dfrac{\left\{\mathrm{Bel}_k(1) \bullet \prod_{j=2}^{n}\left[\mathrm{Bel}_k(j) + \mathrm{Ign}_u(j)\right] + \sum_{j=1}^{n-1}\prod_{i=1}^{j}\mathrm{Ign}(i)\right\}}{\sum_{k=1}^{K}\left\{\mathrm{Bel}_k(1) \bullet \prod_{j=2}^{n}\left[\mathrm{Bel}_k(j) + \mathrm{Ign}_u(j)\right] + \sum_{j=1}^{n-1}\prod_{i=1}^{j}\mathrm{Ign}(i)\right\} + \prod_{j=1}^{n}\mathrm{Ign}(j)} & \text{if } n > 1 \end{cases} \qquad (25)$$

where $\mathrm{Bel}_k(n)$ is the belief associated with element *k* of the frame of discernment by sensor *i* in the time period *n*. $\mathrm{Ign}_i(n)$ is the ignorance (uncommitted belief) declared by sensor *i* in the time period *n*.

Finally, the upper and lower uncertainties must be computed from the belief function. Letting the power set be $\{D_m\}$ after Dempster's rule is applied, then the ***lower bound*** of the uncertainty is the **support**, *S*, and is the sum of all beliefs assigned the element itself and any elements that are subsets of it;

$$S(D_j) = \sum_k \mathrm{Bel}(D_k) \qquad (26)$$

where each D_k must be a subset of D_j.

The ***upper bound*** of uncertainty is the **plausibility** , *Pl*, which is defined to be 1 minus the support of $\overline{D_j}$ which is the union of all elements whose intersection with D_j :

$$Pl(D_j) = 1 - S(\overline{D_j}) \qquad (27)$$

where $D_j\overline{D_j} = \phi$ is the null event.

The **time(measurement number)** for which a decision can be made is 1) ***BELIEF*** (Pr{x}>0.5): or as soon as all but the identified plausible objects are not plausible, 2) ***PLAUSIBILITY*** (all Pr{x} < 0.5). *Note*: probability is assigned to events or situations, whereas, beliefs are assigned to proposed situations. The meaning of the belief measure is the reliability of receiving the information and its meaning, and the integrated belief can be feed back to enhance situational awareness (Figure 3 vs. Figure 2).

3.4.2 Modified DS with Probability Updates

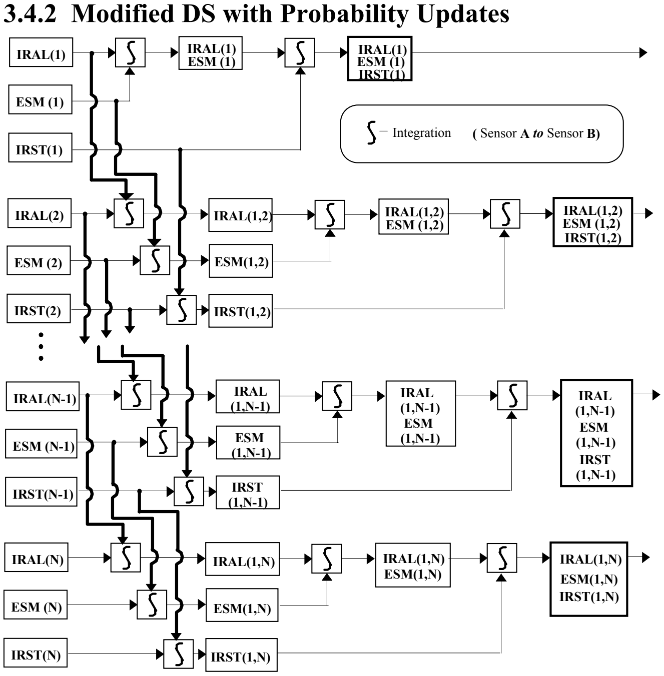

Figure 2. Dempster-Shafer Reasoning ***Without*** Feedback.

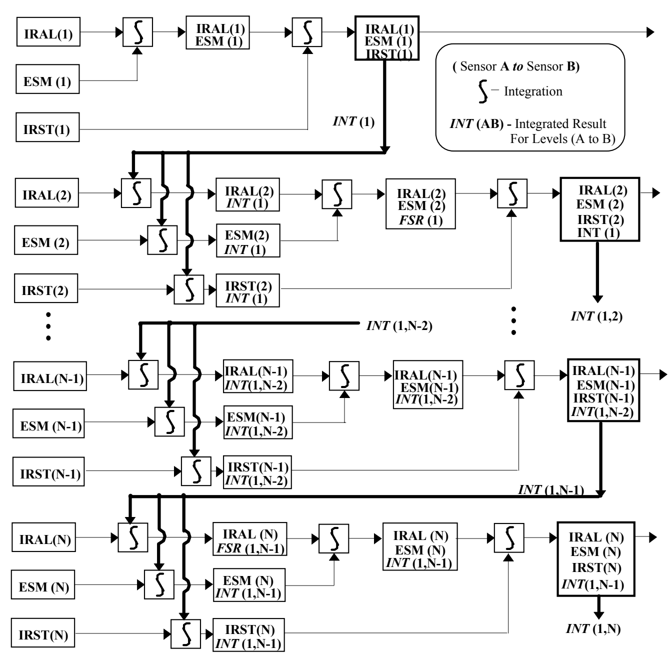

Figure 3. Dempster-Shafer Reasoning ***With*** Feedback.

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3.5.1 Dempster-Shafer Analysis of IRAL & ESM Sensor

Each entry has two elements: a *belief value* and *an n-bit vector* that represents the proportion to which the belief is attached. The row-column intersections of an un-normalized belief value is the product of the beliefs.

$$Bel_d(B) = \text{Bel}_{ESM}(C)\,\text{Bel}^T_{IRAL}(D) \tag{28}$$

where:

***Bel*$_d$(B)** is the matrix of beliefs that result from Dempster's rule on the frame of discernment, B.

Bel$_{ESM}$(C) is the column vector of beliefs from the ESM sensor with Frame of Discernment, C.

Bel$^T_{IRAL}$(D) is the transpose of the column vector of beliefs from the IRAL sensor on its frame of discernment, D.

***Bel*$_{ij}$ = C$_i$D$_j$.**

The ESM(or IRST) assigns the remaining Belief as:

$$\text{Bel}_{ESM}(\text{Bits}(1,0)T_k) = \begin{cases} \dfrac{P_{ESM}(D|T_k)}{\sum_k P_{ESM}(D|T_k)} & \text{if } p_{ESM} > 0.5p_{max} \\ 0 & \text{otherwise} \end{cases} \tag{29}$$

and the plausibility as:

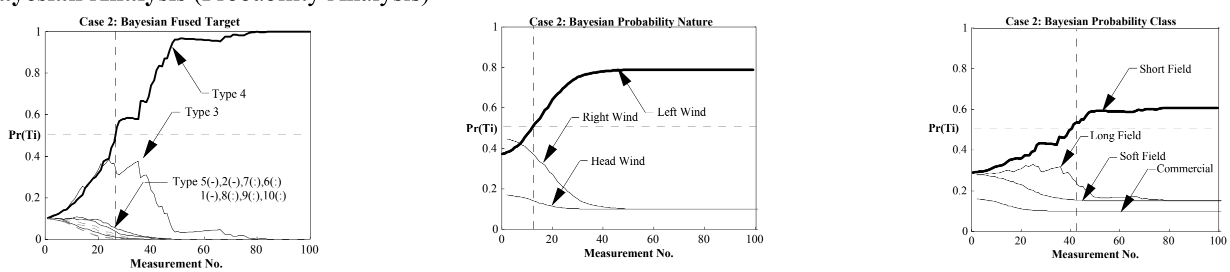
$$\text{Pl}_{ESM}(\text{Bits}(1,0)T_k) = \begin{cases} \dfrac{P_{ESM}(D|T_k)}{\sum_k P_{ESM}(D|T_k)} & \text{if } p_{ESM} < 0.5p_{max} \\ 0 & \text{otherwise} \end{cases} \tag{30}$$

where Bel$_{ESM}$(Bits(1,0),T$_k$) represents the bit vector associated with the k^{th} target runway type and $P_{ESM}(\text{data}|\,T_k) = P_{max}$ for the most likely T_k. Note that the DS approach uses a truncation point (0.001) to terminate the iteration and is called ***truncated DS*** processing, as it truncates the low belief values and assigns that belief to the uncommitted (or ignorance) state.

4.0 SIMULATION RESULTS

A MATLAB program simulates the Bayes, DS, and MDS approaches with measurements from an IRAL, ESM, & IRST.

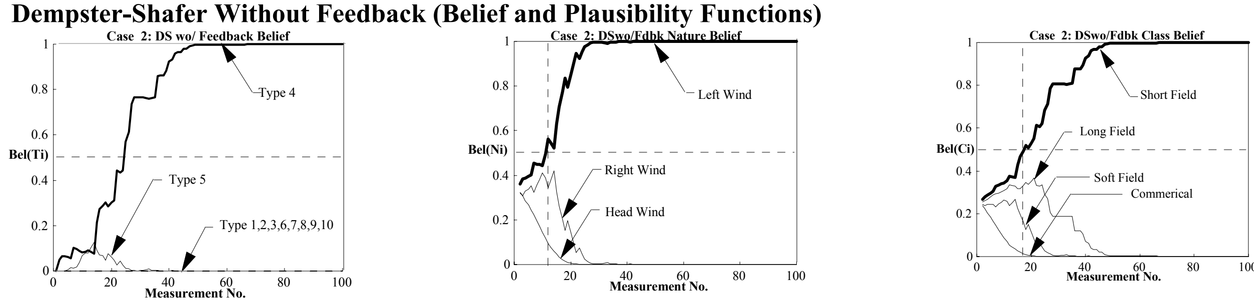
3.1 Bayesian Analysis (Probability Analysis)



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

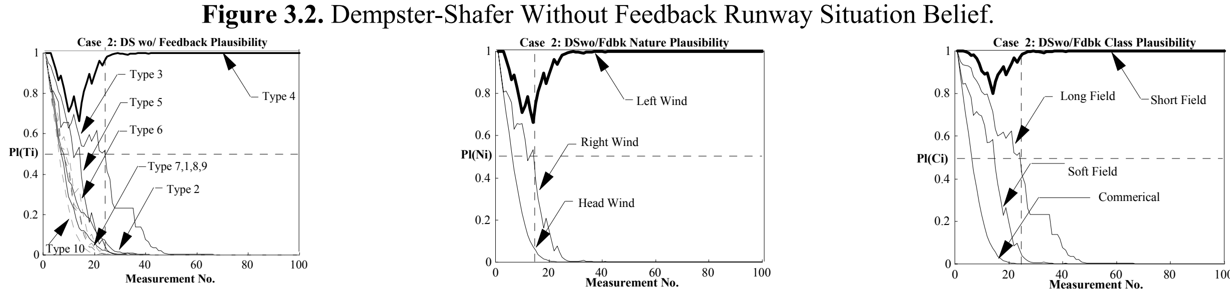
Figure 3.1. Bayesian Runway Situation Identification

3.2 Dempster-Shafer Without Feedback (Belief and Plausibility Functions)



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

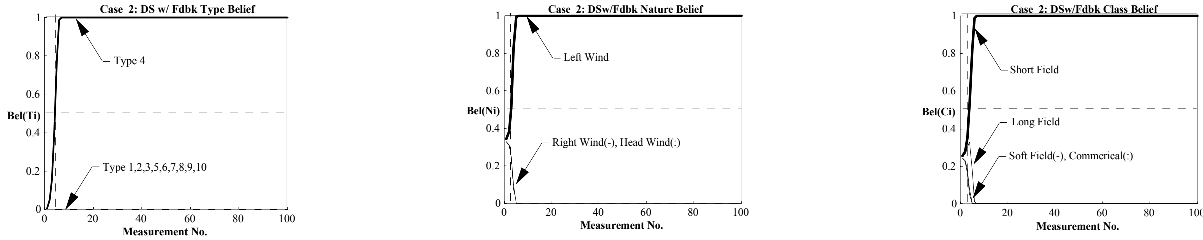
Figure 3.2. Dempster-Shafer Without Feedback Runway Situation Belief.



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

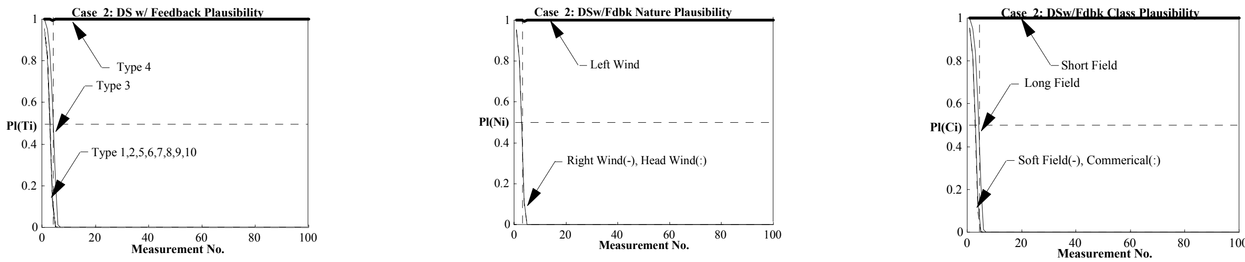
Figure 3.3. Dempster-Shafer Without Feedback Runway Situation Plausibility.

3.3 Dempster-Shafer With Feedback (Belief and Plausibility Functions)



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

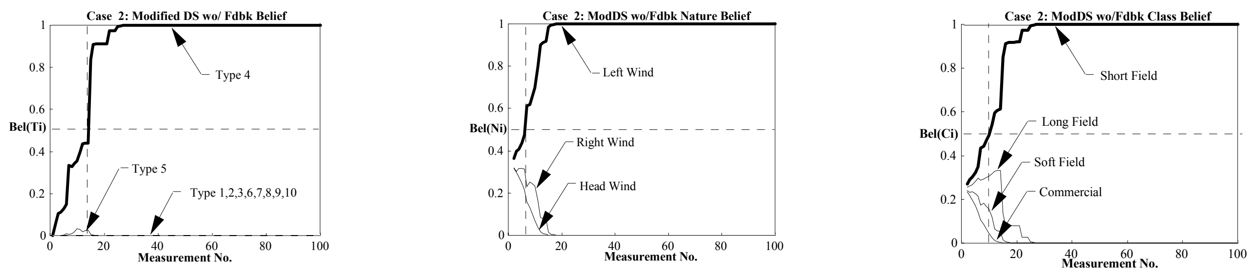
Figure 3.4. Dempster-Shafer with Feedback Belief for Runway Situation Identification.



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

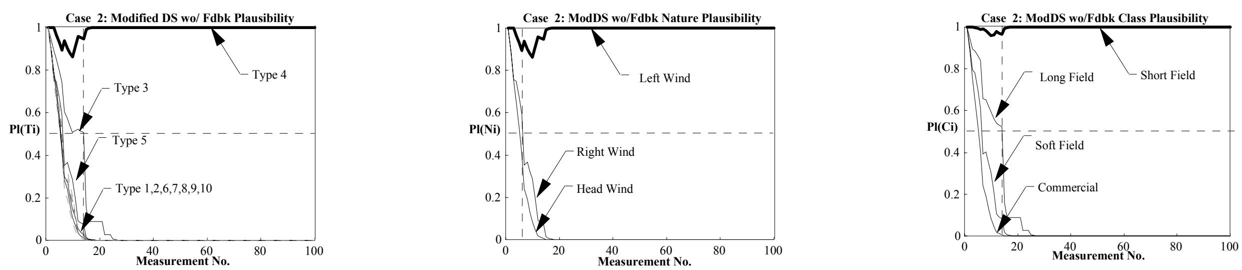
Figure 3.5. Dempster-Shafer with Feedback Plausibility for Runway Situation Identification.

3.4. Modified Dempster-Shafer Without Feedback (Belief and Plausibility Functions)



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

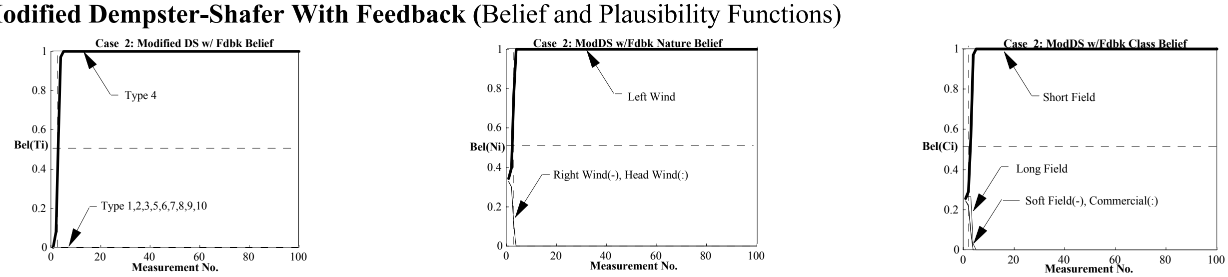
Figure 3.6. Modified Dempster-Shafer without feedback Belief for Runway Situation Identification.



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

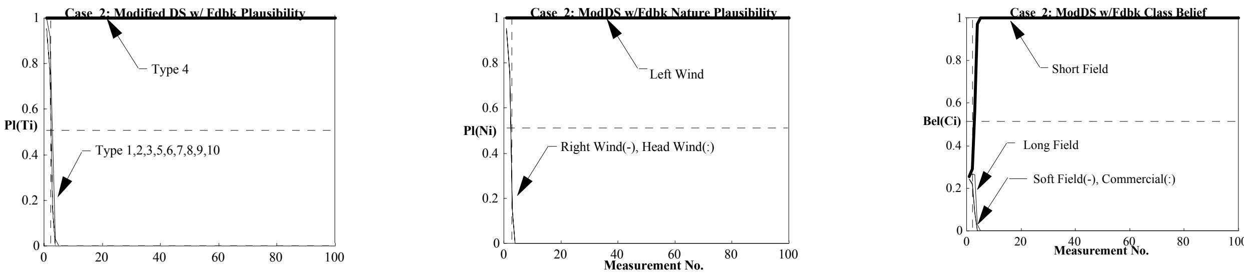
Figure 3.7. Modified Dempster-Shafer without feedback Plausibility for Runway Situation Identification.

3.5 Modified Dempster-Shafer With Feedback (Belief and Plausibility Functions)



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

Figure 3.8. Modified Dempster-Shafer with Feedback Belief for Runway Situation Identification.



Type {1:10}. Nature of Wind (Right, Left, Ahead) Runway Class(Soft, Short, Long, Com)

Figure 3.9. Modified Dempster-Shafer with Feedback Plausibility for Runway Situation Identification.

The results show **Short Field (Class)** and **Left Wind (Nature) ⇒ (Type 4)** for the light aircraft case.

4.0 DISCUSSION and CONCLUSIONS

4.1 Comparisons of Belief & Plausibility Functions

Note that in all the cases, the Belief is less than the Plausibility, or **Bel(A) < Pl(A).** This relationship holds since at the start, the plausibility of any nature, type, or class is possible and the belief is zero. As time goes on, the plausibility of an the identified type remains high and the belief increases; while the plausibility and belief of the other unidentified functions decrease.

Time to Reach Decision	Type	Nature	Class	Type	Nature	Class
Case 1 (Heavy) R, Long						
Bayesian	21	10	28			
	Belief	Belief	Belief	Plause	Plause	Plause
DS Without Feedback	26	9	18	24	8	23
DS With Feedback	6	4	5	7	8	5
MDS Without Feedback	10	9	8	10	8	8
MDS With Feedback	5	4	5	6	3	5
Case 2 (Light) - L, Short						
Bayesian	26	16	43			
	Belief	Belief	Belief	Plause	Plause	Plause
DS Without Feedback	24	13	18	23	16	24
DS With Feedback	5	2	3	5	3	4
MDS Without Feedback	17	7	10	18	8	16
MDS With Feedback	3	2	2	4	3	4

4.2 Comparisons of Bayesian, DS, and Modified DS

The Bayesian and Dempster-Shafer approaches identified the correct nature, type, and class; but the difference is the time in which the correct decision could be rendered. The ***Modified*** **Dempster-Shafer** approach **with feedback** rendered the correct answer ***more efficiently*** than the Dempster-Shafer approaches without feedback, the conventional Dempster-Shafer approach, or the Bayesian approach. Using the MDS with feedback simulates the learned experience of efficient pilot's and may be suitable for the landing and docking of autonomous UAVs.

5.0 REFERENCES

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