A Novel Human-Machine Interface Framework for Improved System Performance and Conflict Resolution

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ABSTRACT

This paper introduces a framework for the conceptualization and design of novel operator-aircraft/unmanned system automated interface concepts that will assist to enhance operator reliance on automated advisories. There is a need to explore new human-machine interface strategies stemming from the proliferation over the past years of accidents due to system complexity, failure modes and human errors. Concepts of **autonomy** establish the foundational elements of the work. We pursue a rigorous **systems engineering process** to analyze and design the tools and techniques for automated vehicle health monitoring, human-automation interface and conflict resolution enabled by innovative methods from Dempster-Shafer theory and reasoning algorithms. The emphasis in this contribution is on conflict resolution arising between the human operator (pilot) and on-system automated apparatus. The enabling technologies for conflict resolution borrow from Dempster-Shafer evidential theory, probabilistic and Game Theory for improved system autonomy and reasoning paradigms. The efficacy of the approach is demonstrated via an application to major drive subsystems of a helicopter and an autonomous hovercraft laboratory prototype.

1. INTRODUCTION

There is an urgent need to improve the autonomy, safety, survivability and availability of such critical assets as aircraft and robotic (unmanned) systems that are subjected to internal and/or external threats in the execution of a mission. It has been well documented over the past years that human error is a major cause of class A aircraft mishaps. Moreover, on-board equipment malfunctions, incipient failures and environmental stresses contribute to aircraft accidents. (Hoc, 2000) Most complex systems of interest are now designed and operated with on-board capability to monitor and assess the health of their critical components/subsystems. Such automated processes issue appropriate advisories to the operator/pilot/ground station to take corrective action and avoid detrimental or even catastrophic events. These automated systems and the human operator are invariably exposed to different evidences that result in conflict or disagreement as to the "best" action required to remedy an emergency situation.

A significant challenge for unmanned systems and manned aircraft relates to their ability to resolve conflicts between the human operator and automated advisories, learn from situational awareness cases, and support the operator/pilot in the execution of a mission. It was suggested by an Autonomous Vehicle Operator (AVO) that, at times, "he's been more overcome by the torrent of information pouring in during a drone flight than he was in the cockpit". During the past decades, research has focused on human machine interface issues with an emphasis mainly on the human collecting information and controlling the system. Apparently, the operator is faced with the problem of "information overflow". More recently, with systems becoming more complex and the information processing ability of machines/systems improving, the machine is called upon to perform the same dynamical and automatic functions as those the human was executing in the past. These processes could be affected by uncertainty in the system or the environment. Hence, there is a need to allocate appropriate functions between the human and the machine to reduce the effects of uncertainty.

2. TECHNICAL APPROACH

The Human-Automation Interface-Conflict Resolution and Decision Support-The constituent modules of the human-machine interface architecture pursued in this paper include an on-board automated system that provides to the human operator the most accurate and reliable information regarding the platform's current and future health state through key performance metrics specific to the vehicle and onboard sensors. These are presented to the operator in a prioritized manner based on mission essential elements. A modified Dempster-Shafer formula is employed to combine conflicting and incomplete information.

The proposed human-machine interface architecture is illustrated in Figure 1. In the top middle of the figure is the aircraft, the targeted test bed. The pilot or operator is shown on the left. The block under the pilot represents the estimation of current system status. The latter is aided by the knowledge base, which, in return, provides an input to the pilot for emergency actions. Similarly, the Data Acquisition (DAQ) module and aircraft health status estimation block are depicted on the right. There are two major information flows, i.e. information collected by the pilot and the automated system, respectively. The pilot observes current environmental conditions, reads the on-board displays, and communicates with the knowledge base. The Automated System (AS), on the other hand, gathers information from the available on-board sensor suite, represented by the DAQ module. The pilot and the AS apply then reasoning strategies based on the information collected and data/information available in the knowledge base. If there is a conflict between the pilot's decision and the AS's advisory, the conflict resolution module attempts to resolve such conflicts using tools from Dempster-Shafer Theory, probabilistic/fuzzy reasoning paradigms. The final recommendation is generated by the Decision Support System and sent back to the pilot as the final "decision maker" for the "best" action to mitigate the current emergency condition.

Particle Filtering for Fault Diagnosis and Failure Prognosis- The proposed fault diagnosis and failure prognosis framework builds upon mathematically rigorous concepts from estimation theory – an emerging and powerful methodology in Bayesian theory called Particle Filtering that is particularly useful in dealing with difficult non-linear and/or non-Gaussian problems. Particle filtering facilitates the estimation of the state (fault) model over consecutive time instants as measurements become available. The particle filtering routines for diagnosis and prognosis are implemented and executed in near real-time and constitute an integrated framework where the results of diagnosis serve as the initial conditions for prognosis in a transparent and efficient manner.

Fault Diagnosis- The particle-filter-based diagnosis framework aims to accomplish the tasks of fault detection and identification using a reduced particle population to represent the state probability density function (pdf). (Orchard, Wu and Vachtsevanos, 2005)This framework provides an estimate of the probability masses associated with each fault mode, as well as a pdf estimate for meaningful physical variables in the system. Figure 2 shows the anomaly detection results based on an RMS feature. The first plot depicts the progression of the feature as a function of time while the second is the probability of failure; the last one shows the baseline and fault pdfs at 5% false alarm rate. The Type II error is 1.1117% at that specific instant of time.

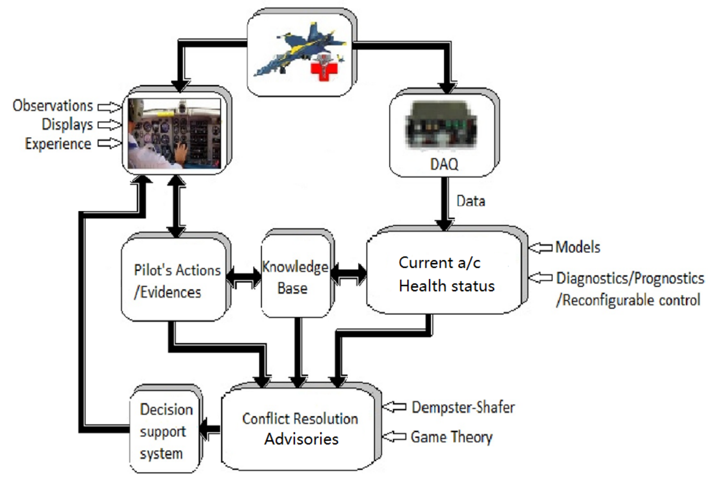

Figure 1. Architecture of human-machine interface

Another performance metric is the Fisher Discriminant Ratio shown at the bottom of the figure.

The "smart" Knowledge Base-A reasoning paradigm called Dynamic Case Based Reasoning (DCBR) that stores cases, matches new cases with stored ones and exhibits attributes of learning and adaptation will be used as the "smart" knowledge base to provide the human operator the ability to interpret automated system outputs correctly and to effectively control the decision making process.

The Pilot/Operator-The pilot/operator, on the other hand, gathers information in a very different way. (Parasuraman & Mouloua, 1996) He/she can exploit a variety of data/information sources, such as displays, alarms - red lights, personal sensing capabilities- the pilot could sense vibrations, temperature rising, noise, etc., visual

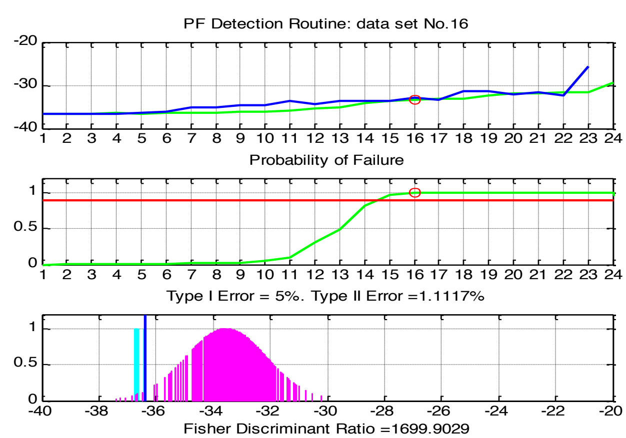

Figure 2. Particle Filtering Routine

observations – look outside the window- rain/ snow, thunder, etc., experience, communication with ground or other aircraft. The pilot gathers information such as oil temperature, fuel pressure, etc. He/she uses this information to assess the current state of the system's health status and to take "initial" actions in the event of an emergency. The operator at this stage may initiate a corrective action or communicate his/her intended actions to the knowledge base. It is understood that timing requirements and sequencing of events in near real-time on-platform are crucial in the final decision making process. The computational requirements burdening the AS are minimized thus allowing for the expedient assessment of the vehicle's state and the application of conflict resolution results.

The Automated System- The Health Management Module-The goal is an advanced integrated reasoning toolset that incorporates justified levels of automated fault accommodation based on prognostic information for enhanced vehicle safety and decision support.

Health and Usage Monitoring Systems (HUMS) acquire on-line in real-time appropriate data and to develop models, algorithms and software that can efficiently and effectively detect faults and predict the Remaining Useful Life (RUL) of failing components with confidence while minimizing false alarm rates. Although the pilot/operator is tasked to use his/her experience, observations and displays to decide on probable causes of an emergency condition and take appropriate initial action, the automated system must perform a series of computationally intensive processes in order to arrive at an advisory for the human operator as to the cause of current adverse conditions and appropriate mitigating strategies. We are introducing a rigorous and verifiable architecture for monitoring and health assessment of critical aircraft systems/components. We outline briefly the major modules of the architecture.

Decision Support System-The decision support system combines these two mass structures derived from the pilot and the automated system using Dempster's rule of combination to arrive at the belief and plausibility for the combined advisory. We are assuming that the final advisory is given to the pilot from the decision support system for action. Moreover, an explanation of how this advisory was derived, i.e. based on what evidence is also provided to the pilot.

3. THE AUTOMATED SYSTEM-PILOT CONFLICT RESOLUTION METHODOLOGY

Conflicts arise between the pilot's intent/commands and automated system commands/advisories. They arise from the different perceptions of the pilot and the automated routines stemming from experience, current data and information available to the pilot and the control architecture which may differ in content, quantity and means for the expedient presentation and follow-up action. The principal task of the Conflict Resolution Module is, therefore, to resolve conflicts between the pilot's actions and those recommended by the automated system.

Conflict resolution is a challenging task that must be addresses methodically in the presence of incomplete evidence, ambiguity and noise. We may apply such methodologies as Dempster-Shafer Theory or Game Theory, among others. In this paper we pursue a conflict resolution method based on Dempster-Shafer theory and specifically Dempster's rule of combination.

Dempster-Shafer Theory-The Dempster-Shafer Evidential Theory is widely used in possibility combination, sensor fusion, artificial intelligence, and conflict resolution areas. (Paksoy & Gokturk, 2011) It allows one to combine evidence from different sources and arrive at a degree of belief that takes into account all the available evidence.

In this formalism a degree of belief, which is also referred to as a <u>mass</u>, is represented as a belief function. Possibility values are assigned to sets of possibilities rather than single events. Dempster-Shafer theory assigns its masses to all non-empty subsets of entities. Application of the Dempster-Shafer Theory requires first and foremost the calculation of the mass functions, as detailed in the sequel.

Assume m_1 and m_2 are two belief function structures on X provided by the pilot and automated system, respectively. m_1 has focal elements $A_1, \cdots, A_k$ and m_2 has $B_1, \cdots, B_p$. We will introduce a modified form of Dempster's rule (Yager, 1987) to combine evidences and avoid counterintuitive results faced by classical methods. Consider two mass functions m_1 and m_2 and define:

$$m = m_1 \perp m_2 \tag{1}$$

where $\perp$ denotes the direct sum and m is calculated as:

$$K = \sum_{\substack{A_i, B_j \\ A_i \cap B_j = \emptyset}} m_1(A_i) m_2(B_j)$$

$$m(\emptyset) = 0$$

$$m(A) = \sum_{\substack{A_i, B_j \\ A_i \cap B_j = A}} m_1(A_i) m_2(B_j), \qquad A \neq \emptyset, X$$

$$m(X) = \sum_{\substack{A_i, B_j \\ A_i \cap B_j = X}} m_1(A_i) m_2(B_j) + K \tag{2}$$

In Dempster's rule, the quantity k is a measure of the degree to which the combined structures disagree with each other. Shafer defines K=log(1-k) as the weight of conflict. So, in Dempster's rule, 1-k represents the normalizing factor needed to assure that the resulting possibility mass satisfies the necessary conditions, i.e. $\sum m(A) = 1$.

Mass function Evaluation- The mass function is the foundation for applying Dempster-Shafer theory to the conflict resolution problem. The estimation of the mass functions is a challenging problem addressed by several investigators without a satisfactory solution from an analytical and computational perspective. The following sections detail its principal components.

Probability based reasoning-Several assumptions are stipulated for this method: (Basir & Yuan, 2007)

1) There are N types of faults, and M features

2) All features are independent from each other

We employ initially the same formulation as in the previous section.

We use the existing data to fit a two-dimensional normal distribution. In this case, as the two features are independent, ρ is equal to 0. So the distribution now becomes:

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left[\frac{(x-\mu_x)^2}{\sigma_x^2}+\frac{(y-\mu_y)^2}{\sigma_y^2}\right]}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_x} e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2}} \cdot \frac{1}{\sqrt{2\pi}\sigma_y} e^{-\frac{(y-\mu_y)^2}{2\sigma_y^2}} = f(x)\cdot f(y) \tag{3}$$

Thus, it is written as the product of two independent one-dimensional normal distributions.

For each fault mode, the histogram is generated and then a

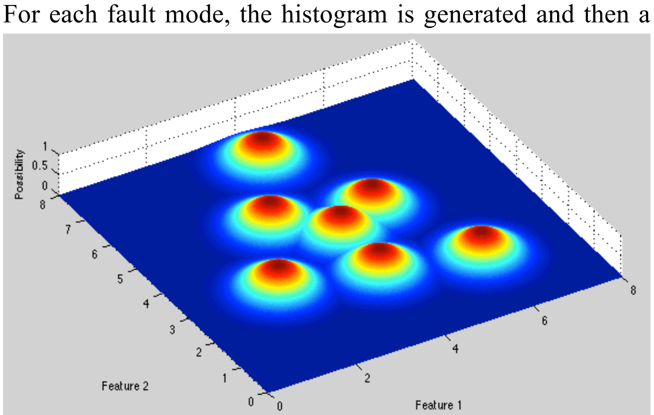

Figure 3. Distributions of fault modes

normal distribution is fitted. Consider next the hypotheses where multiple elements are present. For each hypothesis j we have the label vector L_j. Based on this, the distribution is generated by the following criteria:

$$\begin{bmatrix}\mu_{xj}\\ \mu_{yj}\end{bmatrix} = \frac{\begin{bmatrix}\mu_{x1} & \cdots & \mu_{xM}\\ \mu_{y1} & & \mu_{yM}\end{bmatrix} L_j{}^T}{\|L_j\|_2^2} = \frac{\begin{bmatrix}\mu_{x1} & \cdots & \mu_{xM}\\ \mu_{y1} & & \mu_{yM}\end{bmatrix}\begin{bmatrix}l_1\\ l_2\\ \vdots\\ l_M\end{bmatrix}}{\|L_j\|_2^2} \tag{4}$$

$$\begin{bmatrix}\sigma_{xj}\\ \sigma_{yj}\end{bmatrix} = \frac{\sqrt{\begin{bmatrix}\sigma_{x1}^2 & \cdots & \sigma_{xM}^2\\ \sigma_{y1}^2 & & \sigma_{yM}^2\end{bmatrix} L_j{}^T}}{\|L_j{}^2\|} = \frac{\sqrt{\begin{bmatrix}\sigma_{x1}^2 & \cdots & \sigma_{xM}^2\\ \sigma_{y1}^2 & & \sigma_{yM}^2\end{bmatrix}\begin{bmatrix}l_1\\ l_2\\ \vdots\\ l_M\end{bmatrix}}}{\|L_j{}^2\|} \tag{5}$$

Thus, all the distributions are generated as in Figure 3. For any given states, the actual state vector generated from the sensor suite is represented as: $S = [s_1, s_2, \dots, s_n]$ As in our case, there are only two features, then the S=$[x_0, y_0]$. Define P in a vector form as: $P = [p_1, p_2, \dots, p_{2^M-1}]$

Each element in P is generated by the likelihood S for each distribution:

$$p_i = f_i(x_0, y_0) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left[\frac{(x_0-\mu_x)^2}{\sigma_x^2}+\frac{(y_0-\mu_y)^2}{\sigma_y^2}\right]},$$

$$i = 1,2, \dots 2^M - 1 \tag{6}$$

Normalizing the P vector, the mass vector is derived by:

$$m_j = \frac{p_j}{\|P\|_1}, j = 1,2,\dots,2^M - 1$$

$$M = [m_1, m_2, \dots, m_{2^M-1}] \tag{7}$$

Thus, the mass functions are generated.

We introduce the following Mean Error Bar (MEB) metric:

$$MEB = \int_{t=0}^{t_f} (Pl(t) - Bel(t))dt \tag{8}$$

Or, in discrete form:

$$MEB = \sum_{n=0}^{N} (Pl(n) - Bel(n)) \tag{9}$$

As shown, the belief and plausibility functions give the lower and upper bounds of the possibility function, respectively. The value Pl(t)-Bel(t) stands for the ignorance of the possibility at time t. Usually the possibility is given by the mean of the plausibility and belief functions. If the two values are close, a precise estimate of the possibility function could be given with a small error. Another word, smaller MEB values stands for a more precise estimation. The MEB is, therefore, an appropriate performance metric.

4. THE APPLICATION DOMAINS: HELICOPTER DRIVE SYSTEM

The application domain (in simulation) for the conflict resolution configuration is the Oil-cooler & Intermediate Gearbox (OC-IGB) subsystems of the UH-60 helicopter drive system. The complete drivetrain is shown in Figure 4. The OC-IGB subsystem is highlighted by the red rectangular area. The components include the oil-cooler, the intermediate gearbox, and the tail shaft connecting these components. We define appropriate fault modes and suggest data/observations/displays available to the operator (pilot). On the other hand, we configure the automated system to accomplish sensor data collection and analysis including the diagnostic, prognostic and control modules introduced previously.

An illustrative example-The proposed human-machine interface framework and the conflict resolution routines may be applied at various levels of the system hierarchy. For example, at the system/subsystem level, the pilot and the automated system may disagree (due to different evidence sources presented to each module) as to which subsystem is experiencing a fault/failure mode. Specifically, may be considering with certain confidence that the Intermediate Gear Box (IGB) of the helicopter's drive system is subjected to a fault. The pilot's conclusion stems from his/her perception/experience, the sensed vibration levels, panel

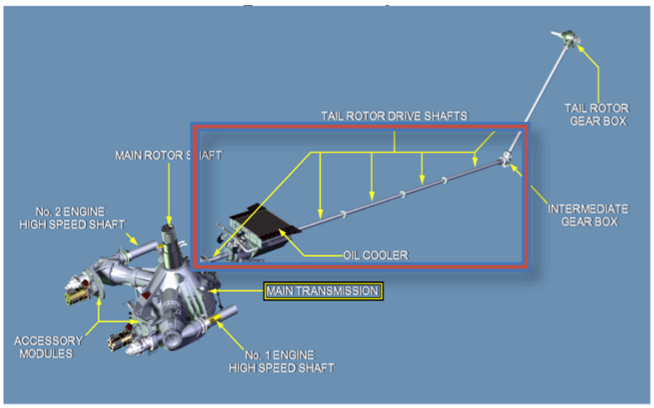

Figure 4. Drivetrain of the UH-60 helicopter

indicators, displays, etc. On the other hand, the automated system is suggesting that the faulty component is the oil cooler. Sensor measurements collected and analyzed by the automated system include oil cooler temperature levels, vibration signals, etc. Shaft coupling in the drive system is one of the main causes for ambiguity/uncertainty corrupting the evidence and resulting in inaccurate allocation of faults. At the component level, the pilot may be surmising, on the basis of the current evidence, that a bearing in the oil cooler assembly is subjected to a fault while the automated system is concluding that the rise in the oil cooler temperature is causing another component to fail.

Features or Condition indicators (CIs) are extracted from the data presented to the automated system. The "best" feature(s) constitute the mass function for the automated system expressed in appropriate probabilistic or fuzzy form. A similar approach is pursued to express the pilot's assertion as a mass function.

We employ the crack level evaluation as a demonstration of the possibility combination for conflict resolution. Consider the crack level as the fault mode for the automated system. We break it down for simplicity into three categories: Light (wear level 0-1inch), Medium (wear level 1-2 inches) and Severe (wear level 2-3 inches). The automated system applies the distance-based algorithm. On the other hand, the pilot senses the vibration in Area 1 (oil cooler) and 2 (IGB). This possibility can be represented as a mass value as well. For instance, the pilot decides: the probabilities of vibration in Areas 1 and 2 are 70% and 90%, respectively. Thus, the possibility of vibration in the oil cooler bearing area is $70\%\times 90\% = 63\%$. Based on the Bayesian allocation theorem, this possibility value is allocated uniformly to medium, severe, medium/severe, by:

$$\mathrm{m(Medium)} = \mathrm{m(Severe)} = \mathrm{m(Medium/Severe)} = \frac{\mathrm{p}}{3}$$

So the mass function for the pilot is shown in the Table 1. Then, the decision support system combines these two mass structures using Dempster's rule of combination to arrive at the belief and plausibility functions using the MEB metric, as suggested previously.

Table 1. The mass function for the pilot

Hypothesis	**M(H)**
Light	0.37
Medium	0.21
Severe	0.21
Light/Medium	0
Light/Severe	0
Medium/Severe	0.21
Any	0

It is evident that the combined result decouples the oil cooler bearing and IGB. Meanwhile, it could provide rigorous estimates of the probabilities for each fault mode.

5. RESULTS

The data used in this case study is generated by a MATLAB routine. It consists of sensor values and status evaluations for 37 time indexes. The features discussed above and the status evaluations are extracted from the data set. The pilot's judgment is based on his perception while the Automated System collects the pre-processed data and provides the advisories. Then, the decision support system reads the estimations and gives the combined reasoning result. The simulation procedure is also carried out in MATLAB.

5.1 Oil Cooler Bearing Crack Level Prognosis (Dempster-Shafer Result)

The pilot and the automated system can both do the prognosis based on the information they collected. For instance, in our case, the pilot and the automated system can collect information from time 0 to time 3.2. And based on these information to predict the 3.2 to 15 system situation, as shown in Figure 5.

The upper figure is generated by the pilot and the lower one belongs to the automated system. The lower edge of the figure is the threshold of severe crack. So the pilot believes

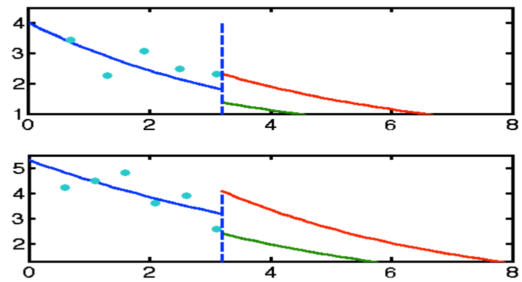

Figure 5. Particle Prediction result by pilot and automated system

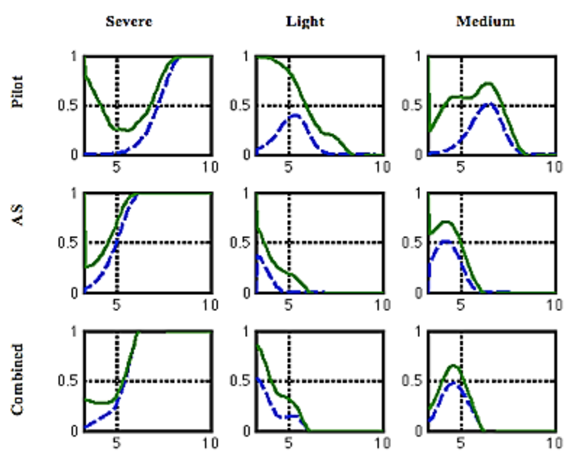

Figure 6. Probability estimated by the pilot, Automated System and the Combined Result

the time for severe crack could be between 4.5 and 6.5. However, the Automated System says the time should be between 5.5 and 8, with a confidence level of 90%. Here comes the conflict between the two reasoning route. So we apply the conflict resolution here to get a combined result, as shown in the Figure 6. In this figure we can see at the time 6 the crack level should be severe with a confidence level higher than 50%. However at time 5 the condition should be light or medium with a confidence level higher than 70%, with is higher than both the pilot and automated system's judgment. This is an example of resolving the conflict.

The MEB is calculated as shown in the Table 2. The table illustrates that the combined result has much smaller MEB than the pilot or AS separately implying that the combined result reduces the risk, or ignorance, significantly.

Table 2. MEB result for each reasoning Routine

MEB	Pilot estimated	AS estimated	Combined Result
Light	0.2237	0.0805	0.0480
Medium	0.3037	0.0842	0.0751
Severe	0.2152	0.0841	0.0486
Average	0.2475	0.0829	0.0572

5.2 Game Theory Result

First, we map the status evaluation to the action set based on the following table. Here, Action 1 stands for "continue flying" implying that no action is required. Action 2 stands for "prepare to land", which means that maintenance action must be taken after the vehicle reaches its destination. Action 3 stands for "land the aircraft immediately", which means that the aircraft's condition is severe and the pilot must land the vehicle immediately.

Since the automated system monitors the pilot's suggested action(s) automatically, it knows only what action the pilot is taking but not why he takes this particular action and its corresponding probability. Thus, the automated system will evaluate the current status and will estimate the corresponding probability. For example, we are to evaluate the risk for the automated system suggesting Action 1 but the pilot takes Action 3. There are four conditions that recommend Action3 to be taken by the pilot:

Table 3. Conditions which Recommend Action 3

Condition	IGB	Oil cooler bearing	Probability
1	Faulty	Light	$Pr_1 = p_{32} \times p_{21}$
2	Faulty	Medium	$Pr_2 = p_{32} \times p_{22}$
3	Faulty	Severe	$Pr_3 = p_{32} \times p_{23}$
4	Normal	Severe	$Pr_4 = p_{31} \times p_{23}$

Then, referring to the risk table below:

Table 4. Risk Table

Components	Status	Risk for Action1	Risk for Action2	Risk for Action3
Oil cooler bearing Crack	Light	0	0	0
	Medium	16	0	0
	Severe	31	14	0
IGB	Normal	0	0	0
	Faulty	42	17	0

The risk for taking Action 1 is:

$$R_{31} = \sum_{i=1}^{4} Pr_i\, r_i = 42Pr_1 + 58Pr_2 + 73Pr_3 + 31Pr_4$$

The cost corresponding to each action is estimated as follows:

Table 5. Cost Table

Action	Action 1	Action 2	Action 3
Cost	0	25	50

The cost for taking Action 1 is, of course, zero. The proposed formulation provides thus both cost and risk information. The pilot's suggested action and the AS's advisory are illustrated in Figure 7.

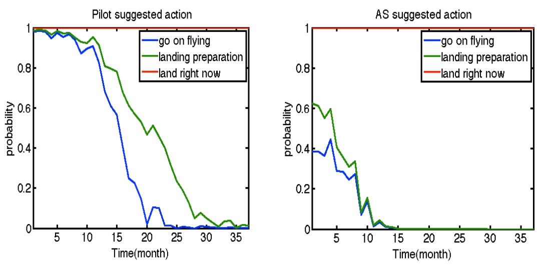

Figure 7 Suggested actions given by the pilot and Automated System

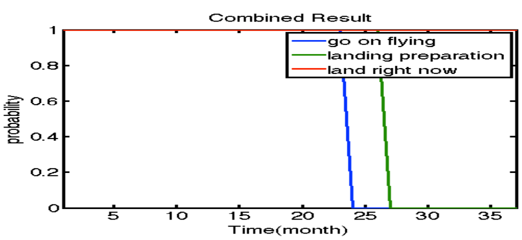

Figure 8 Combined Advisory

Generally, the situation estimated by the automated system is more severe than that of the pilot. Thus, the action suggested by the automated system tends to cost more and is more likely to avoid some severe risks. The combined result, which is the optimum under the given payoff function, is shown in Figure 8.

6. CONCLUSION

In this paper we have described a novel human machine interface framework for conflict resolution. The methodologies applied are modified Dempster-Shafer Theory and Game Theory based conflict resolution methodology. The result shows that the combined result has a better performance than the assessment provided by the pilot or the automated system.

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BIOGRAPHIES

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