Dissonance Between Multiple Alerting Systems Part I: Modeling and Analysis

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***Abstract*—The potential for conflicting information to be transmitted by different automated alerting systems is growing as these systems become more pervasive in process operations. Newly introduced alerting systems must be carefully designed to minimize the potential for and impact of alerting conflicts, but little is currently available to aid this process. A model of alert dissonance is developed that provides a theoretical foundation for understanding conflicts and a practical basis from which specific problems can be addressed. Part I establishes a generalized methodology to analyze dissonance between alerting systems, and Part II exercises the principles and presents methodologies to avoid and mitigate dissonance. In Part I, we develop a generalized state-space representation of alerting operation that can be tailored across a variety of applications. Based on the representation, two major causes of dissonance are identified: logic differences and sensor error. Additionally, several possible types of dissonance are identified. A mathematical analysis method is developed to identify the conditions that cause dissonance due to logic differences. A probabilistic analysis methodology is also developed to estimate the probability of dissonance originating due to sensor error.**

***Index Terms*—Alerting systems, dissonance, modeling, probabilistic analysis, sensor error.**

I. Introduction

AUTOMATED alerting systems are becoming increasingly pervasive in time- and safety-critical operations, with applications spanning aerospace vehicles, automobiles, chemical and power control stations, air traffic control, and medical monitoring systems. As these applications are pushed toward higher safety and capability, new alerting systems have been introduced to provide additional protection from hazards. Accordingly, there has generally been an evolutionary, incremental addition of alerting systems to these applications over time. Because it is costly to completely redesign and recertify automation, new alerting systems are typically independent enhancements that do not directly affect the operation of existing subsystems.

The addition of alerting systems to an already complex operation carries several liabilities [1]. First, there is an increase in the amount of information processing required by the human operator, who now must be trained and able to respond rapidly to more information. There is also a potential for simultaneous alerts from the different systems, possibly overloading or confusing the human. These alerts could also be conflicting in the sense that the information they provide suggests different actions be taken to resolve problems.

In the late 1990s, Pritchett and Hansman explored the concepts of *consonance* and *dissonance* between an alerting system's decisions and a human operator's internal model of a threat situation [2]. Their work and observed incidents in the field have shown that a mismatch or dissonance between the human and automation could lead to undesirable behavior from the human including increased delay in taking action, failure to take action at all, or even implementing an action contrary to the automation's command. These human operator responses may lead to accidents or to inefficiencies due to taking unnecessary action. In the long run, human operators may begin to distrust the alerting system.

Unfortunately, dissonance has already produced a catastrophe. On July 2, 2002, a mid-air collision occurred between a Russian passenger jet and a DHL cargo jet over Germany, killing 71 people. This accident exposed a dissonance problem between an on-board alerting system called the Traffic Alert and Collision Avoidance System (TCAS) and an air traffic controller. According to the German air accident investigation agency, the pilots on the Russian passenger jet received conflicting information from TCAS (which commanded them to climb) and the air traffic controller (who commanded them to descend) [3]. This conflict is a likely contributing factor to the accident. Other similar incidents have occurred recently, including a near-miss in which two wide body jet transports came within an estimated 10 m of each other over Japan in 2001.

Dissonance is likely to be even more problematic when there are multiple automated systems that are not synchronized. The dissonance between a human command and automation may have a chance to be resolved through communication between the humans. But if two on-board alerting systems give dissonant commands to the pilot, it is hard to get additional information from the alerting systems to resolve the dissonance.

Alerting systems on jet transport aircraft, for example, have become more prevalent and complex over the last several decades. In the era of "steamgauge" RD aircraft that relied on electromechanical instruments (before the 1980s), nearly all alerting functions on aircraft were used to monitor autoflight controls and internal components such as engines, hydraulics, or electrical systems. One comprehensive study in 1977 found over 500 different alert displays and functions on the Boeing 747 flight deck [4]. The study also showed a history of exponential growth in the number of alerting functions on board aircraft.

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Since the 1970s, with improved sensor and communication capabilities, aircraft alerting systems have been increasingly focused on external threats such as terrain, other air traffic, and weather. Several of these external-hazard systems are now being augmented by the addition of newer, more capable alerting systems. The Ground Proximity Warning System (GPWS), for example, was mandated on U.S. transport aircraft in the mid-1970s. GPWS uses measurements of the height of the aircraft above terrain to predict whether there is a threat of an accident, and is susceptible to occasional false alarms or late alerts. In the late 1990s the Enhanced Ground Proximity Warning System (EGPWS) was introduced to provide earlier and more accurate warnings of terrain threats. EGPWS uses an on-board terrain database and includes a graphical display of the terrain field around the aircraft. Due to cost and certification issues, GPWS has been retained on aircraft and EGPWS has been added as a separate, independent system that does not change the operation of GPWS. The result, however, is that there are now two separate systems, each monitoring terrain threats and each with different alert threshold criteria and displays. It is then possible to have dissonant information provided to a pilot from EGPWS and GPWS for the same terrain situation. For example, EGPWS could command a pilot to climb while GPWS does not rate the terrain as a threat.

Another example of alert proliferation is the recently-proposed Airborne Conflict Management (ACM) system which must operate in conjunction with the existing Traffic Alert and Collision Avoidance System (TCAS). TCAS has been mandated on U. S. transport aircraft since the early 1990s. It uses range, range rate, altitude, and altitude rate between two aircraft via transponder messages. Initial concepts and specifications of ACM have been drafted by a joint industry/government /academic subcommittee [5]. ACM uses an improved data link to enable longer look-ahead times than is possible with TCAS. The different surveillance methods used by TCAS and ACM may result in dissonance. Alerts from ACM should be harmonized with alerts from TCAS and vice-versa.

To date, management of potential dissonance between systems has occurred without a structured understanding of the specific issues involved. The identification of the potential for dissonance and the development of mitigation methods would be greatly facilitated through the application of a coherent, formal model that articulates the design issues. Such a model would have three benefits. First, it would aid in understanding the different types of dissonance that may occur. Second, the model would help in identifying when or where the different types of dissonance could occur in a given operation. Third, the model may be used to design and evaluate mitigation contingencies to prevent or preclude dissonance from occurring.

This paper (Part I) presents a formal model of multiple alerting system interactions that can be used to identify and describe dissonance. Two major causes of dissonance are identified, and several different types of dissonance are defined. Mathematical methods for analyzing dissonance situations are then presented to help in identifying when or where the different types of dissonance could occur in a given operation. The contribution of logic differences to dissonance can then be compared against the contribution of sensor error. A hybrid model is developed in a companion paper (Part II) to analyze the dangerous consequences of dissonance. In Part II, additional methods are described to avoid and mitigate dissonance.

II. Model of Multiple Alerting System Dissonance

A significant body of research has focused on the design and use of automation, with the goal of determining how automation should be implemented to work harmoniously with the human operator [6]–[9]. Endsley, for example, presents arguments that the human's preconceptions and mental models have a direct effect on how automation improves or degrades situation awareness (SA) [6]. Automation, then, must be carefully designed and implemented to support the human. If not properly applied, automation can degrade SA by reducing the human's involvement in monitoring and control functions.

We move into the issues specifically related to dissonance between two or more alerting systems. The focus here, then, is on the automation, yet it is critical to remember that ultimately it is the human's understanding and interpretation of the automation's displays that affect whether dissonance has an impact. Furthermore, we focus on complex alerting systems that may include several levels of threat assessment and dynamic commands or guidance information provided to the operator. This is in contrast to conventional analysis based on signal detection theory, for example, where there is a known signal and a binary alerting decision to be made [10]. The complex nature of the systems discussed here required that new tools be developed for analysis and design.

A generic state-space representation of the information flow of two alerting systems in a dynamic environment is shown in Fig. 1. Additional alerting systems could be incorporated into this representation without loss of generality. To help illustrate the application of the representation to a specific alerting problem, TCAS is used here as a case study.

From a mathematical standpoint, we denote $\mathbf{x}$ as the state vector representing the complete set of physical parameters that describe the dynamics of a hazard situation. In the case of TCAS, for example, $\mathbf{x}$ represents the three-dimensional position and velocity vectors of each aircraft involved. Next, hazard space is defined as that region in state-space where an undesirable event would occur. Depending on the application, hazard space could involve, for example, the region in space where two aircraft are co-located or a region in which excessive temperature or pressure would harm a chemical process.

On the left of Fig. 1, the process' dynamics are determined from a generalized function, F, of the current state $\mathbf{x}$, operator's inputs $\mathbf{u}$, and modeling or process dynamic uncertainties ξ

$$\dot{\mathbf{x}} = F(\mathbf{x}, \mathbf{u}, \xi). \quad (1)$$

We include in F internal automation that controls the process based on its state. This allows us to focus more directly on just those inputs which arise from the human operator, $\mathbf{u}$, due to alerting system information. The input $\mathbf{u}$ could include manual control movements from the operator or human-directed inputs to automation systems such as an autopilot.

All alerting systems generally perform four functions, (see Fig. 1) monitoring, situation assessment, attention-getting, and

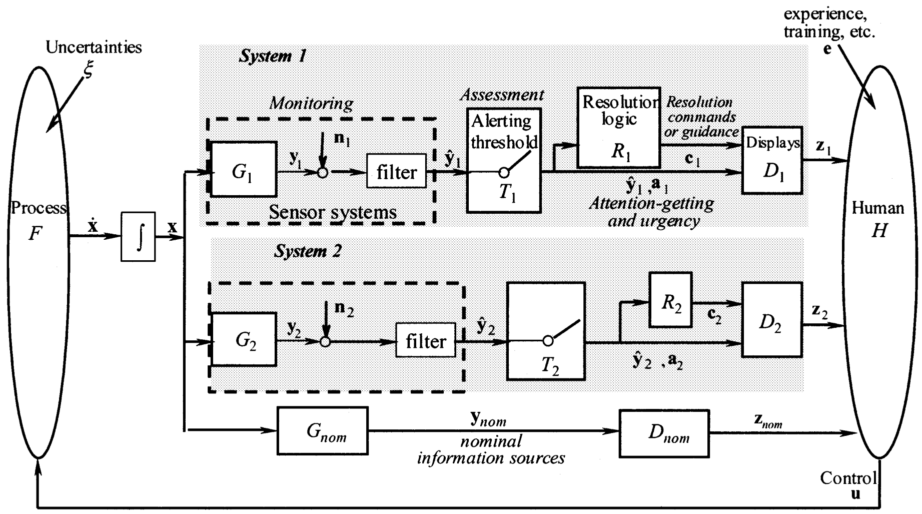

Fig. 1. Generalized state–space representation of multiple alerting systems.

problem resolution. In general, the complete state vector $\mathbf{x}$ is not available to the alerting system logic, but is observed through a set of sensors. The resulting information that is observable to the alerting system is included in the vector $\mathbf{y}$. The alerting systems use possibly different sets of observable states defined by different functions G_i operating on $\mathbf{x}$. As shown in Fig. 1, for the ith alerting system

$$\mathbf{y}_i = G_i(\mathbf{x}). \quad (2)$$

For TCAS, $\mathbf{y}$ is a vector including the range, range rate, relative altitude, and relative altitude rate between two aircraft [11]. Uncertainties in the estimates are modeled through a noise input vector $\mathbf{n}$. We will denote $\hat{\mathbf{y}}$ as the measurement of vector $\mathbf{y}$ corrupted by noise $\mathbf{n}$.

Using the information in $\hat{\mathbf{y}}$, each alerting system applies a set of threshold functions or other logic, T in Fig. 1, to map the situation into an alertness level or *alert stage*. The alert stage is represented by the vector $\mathbf{a}$, and specifies the level of threat or urgency according to that alerting system

$$\mathbf{a}_i = T_i(\hat{\mathbf{y}}_i). \quad (3)$$

The logic used by the alerting system to determine the appropriate alert stage and to provide guidance may vary from simple thresholds based on exceeding some fixed value to more complex algorithms involving a number of states. Many alerting systems work with two stages, i.e., nonhazardous and hazardous. More complex systems use a series of stages, each corresponding to a higher level of danger and urgency. For example, there might be three alert stages for a collision warning and avoidance system: 1) no alert, 2) proximate traffic advisory, and 3) immediate collision warning.

Alerting systems may categorize both the status of each individual hazard under observation, and also specify an overall threat level. TCAS does this, for example, by using different graphical icons depicting the threat posed by each nearby aircraft on a traffic display. Additional aural and visual displays are then used to indicate the overall threat level and whether any action is required. Thus, there may be two different types of alert stage, one for each individual hazard and one for the overall system. The *hazard alert stage* is defined as a discrete categorization of the level of threat posed by a given hazard under observation by a system. The *system alert stage* is the resultant overall level of threat posed by all the hazards under observation by that system. In TCAS, the system alert stage is equal to the maximum of all individual hazard alert stages. That is, the system as a whole takes the worst-case threat and uses its threat level. It could be desirable in other applications, however, to use a different method of translating hazard alert stages into system alert stages.

With TCAS, there are four *hazard alert stages*:

Stage 0 $=$ No threat. The other aircraft is denoted by a hollow white diamond on the display.
Stage 1 $=$ Proximate traffic. The other aircraft is shown as a filled white diamond on the display.
Stage 2 $=$ Caution. The other aircraft is shown as a solid yellow circle.
Stage 3 $=$ Warning. The other aircraft is shown as a solid red square.

There are three corresponding *system alert stages* for TCAS.

Stage 0 $=$ No threat. No additional information is provided.
Stage 1 $=$ Traffic advisory (TA). A master caution light is illuminated in amber and an aural “traffic, traffic” alert is issued in the cockpit. Stage 1 is active if there is a caution hazard stage active but no active warning hazard stages.
Stage 2 $=$ Resolution advisory (RA). A master warning light is illuminated in red, an aural resolution command is issued (such as “climb! climb!”) and the required climb angle or climb rate is shown on a cockpit display. Stage 2 is active if any hazard is in the warning stage.

Based on the alert stage and on the other information on the situation, the alerting system may produce resolution information, $\mathbf{c}$ in Fig. 1, according to the resolution logic R

$$\mathbf{c}_i = R_i(\hat{\mathbf{y}}_i, \mathbf{a}_i) \quad (4)$$

TABLE I
ALERTING SYSTEM INDICATED DISSONANCE TYPES

Indicated Dissonance Type		**Example Dissonant Situation** *System 1*	*System 2*
Alert Stage	system alert stage	no threat	warning
	hazard alert stage	aircraft A is a threat	aircraft B is a threat
Resolution	dimension	turn	climb
	polarity	climb	descend
	magnitude	turn 5°	turn 30°

The vector $\mathbf{c}$ includes the type of resolution action to be performed (e.g., turn or climb) and the magnitude of that maneuver. There are a variety of forms of resolution commands, depending on the complexity of the maneuver to be performed. Problem resolution may also be performed either explicitly or implicitly by the alerting system. In explicit systems, additional command or guidance information is presented to the operator. This may be a verbal message (e.g., "climb!") and/or may include a visual display indicating the type of action to be taken and the aggressiveness with which that action should be taken. In more advanced systems, continuous guidance may be provided to aid in the resolution action. In implicit systems, the human operator may have a trained response to a particular alert stage, or may just decide at that time what action is most appropriate.

Given all the possible combinations of alert stages and command types, it is clear that there is a rich design space for alerting systems. As a consequence, it is possible that two different alerting systems will apply different alert stage or command definitions to a similar problem. This may lead to dissonance as is discussed in a later section.

Referring back to Fig. 1, $\mathbf{z}$ is the vector of complete information displayed to the human operator by the alerting system. In general, $\mathbf{z}$ includes signals designed to attract the operator's attention, the alert stage, and information to resolve the situation. The function D describes the display mapping from the state estimates available to the alerting system $(\hat{\mathbf{y}})$ to the information provided to the human operator $(\mathbf{z})$ based on the alert stage $(\mathbf{a})$ and resolution information $(\mathbf{c})$.

$$\mathbf{z}_i = D_i(\hat{\mathbf{y}}_i, \mathbf{a}_i, \mathbf{c}_i). \tag{5}$$

For TCAS, the information in $\mathbf{z}$ includes a traffic display in the cockpit, aural messages, lights, and any resolution command and guidance information.

In addition to the alerting systems, there may be other, nominal information paths by which the human operator obtains information about the controlled process and the environment. This information builds the human's internal model of the situation—a model that may conflict with the conditions implied by alerting systems. Nominal information is included in the vector $\mathbf{y}_{\mathrm{nom}}$, which is then modified by the nominal displays D_{nom} as shown on the bottom in Fig. 1. Cockpit instruments, air traffic control communications, views through the windscreen, vestibular inputs, and aeronautical charts are examples of nominal information sources for a pilot. The operator is also affected by other factors such as the pilot's internal model of the situation, knowledge of the alerting system's role, prior training, fatigue, and previous experience, modeled with parameter $\mathbf{e}$ in Fig. 1. Past exposure to false alarms, for instance, has been observed to be a factor in delaying responses to alerts [12]–[16]. This modifying information is included in the vector $\mathbf{e}$ in Fig. 1. The function H on the right in Fig. 1 then maps the observable states (via all the alerting systems and nominal information sources) to the control inputs $\mathbf{u}$. That is

$$\mathbf{u} = H(\mathbf{z}_{\mathrm{nom}}, \mathbf{e}, \mathbf{z}_1, \mathbf{z}_2). \tag{6}$$

Ultimately, it is how the inputs to the pilot (as contained in $\mathbf{z}_{\mathrm{nom}}, \mathbf{z}_1, \mathbf{z}_2$, and $\mathbf{e}$) are used to develop a control strategy that determines whether there is dissonance between the information elements being used. In this context, Pritchett and Hansman's work examined dissonance between $\mathbf{z}_1$ for a single alerting system and the nominal information provided to the human in $\mathbf{z}_{\mathrm{nom}}$ [2]. Here, we focus on dissonance across the information provided by two different alerting systems, as contained in $\mathbf{z}_1$ and $\mathbf{z}_2$.

III. Multiple Alerting System Dissonance

Having introduced a general state-space representation for multiple alerting systems, it is now possible to more formally state the types of dissonance that may occur. Dissonance occurs when the alerting systems' states have information content and representations that explicitly suggest different timing of alerts and actions to resolve the hazard [2]. There are two main types of dissonance, *indicated* and *perceived*, that are defined and discussed in the next two sections.

A. Indicated Dissonance

At a high level, all alerting systems can be thought of as mapping a set of estimated states of a controlled process $\mathbf{x}$ into discrete alert stages and discrete or continuous hazard resolution commands $\mathbf{z}$. Indicated dissonance occurs when the information content in $\mathbf{z}$ differs between systems $(\mathbf{z_1} \neq \mathbf{z_2})$. In other words, indicated dissonance occurs whenever a single state maps into multiple alert stages or different resolution commands.

Table I provides a listing of different forms of indicated dissonance. Each row in Table I corresponds to a type of indicated dissonance with certain properties. The right side of the table provides an example situation with two alerting systems in which that category of indicated dissonance is present. For example, having one system command "climb" while a second system commanded "descend" would be a resolution polarity conflict.

Each of these forms of indicated dissonance is discussed in more detail below.

Breaking $\mathbf{z}$ into its components, first consider indicated alert stage dissonance (first row of Table I). For example, EGPWS and GPWS are both alerting systems for terrain. EGPWS is designed to provide an earlier warning of terrain proximity than GPWS. So, usually the alert stage from EGPWS is at an equal or higher level than that from GPWS. There is then often some indicated dissonance since two systems are in different alert stages. As is discussed in the next section, however, this indicated dissonance may not have a significant effect on the operator.

Another type of indicated dissonance can occur when there is a difference in the hazard alert stage for a given threat, even if the system alert stages are consistent (second row of Table I). This could happen, for example, in a case with two traffic alerting systems monitoring two different aircraft, A and B. If system 1 rates aircraft A as a low threat and aircraft B as a high threat while system 2 does the opposite, then both systems may agree with the same high-threat system alert stage, but the underlying hazard alert stages for each threat are different. The operator then may distrust one or both systems since they are disagreeing on the specific cause for the system alert stage.

Indicated dissonance can also occur due to the resolution information contained in $\mathbf{z}$. If two commands are in different dimensions, then there is indicated dissonance (e.g., a case where system 1 commands a change in altitude but system 2 commands a change in heading). If two commands are in the same dimension, then dissonance may still be indicated due to different polarities or magnitudes of the commands. If two systems are both commanding a change in altitude, but system 1 commands a climb and system 2 commands a descent, there is clearly indicated dissonance. Or, if system 1 commands a much stronger climb than system 2, there is indicated dissonance. Note that we use the term dimension here in the most general sense; in a chemical process control example, command dimensions could include opening valves, increasing temperature, etc.

B. Perceived Dissonance

A mismatch of information between alerting systems may not result in the perception of dissonance by the human operator. The human ultimately decides whether indicated dissonance translates into perceived dissonance. Adapting Pritchett and Hansman's work, we define perceived dissonance as a situation in which information from two or more alerting systems have content or representations that suggest different timing or actions to resolve a hazard. It would be very complex to formally identify and analyze perceived dissonance. Many factors affect whether indicated dissonance translates into perceived dissonance (e.g., the human operator's previous experience of the alerting systems, internal model of the situation, prior training, etc.), and most of these factors cannot be modeled in a general mathematical form. It is important to gain a better understanding of how differences between the information conveyed to the human ultimately translate into perceived dissonance, and then how that dissonance affects human performance. Critical human factors research is required for a more thorough analysis, but such aspects are beyond the scope of this paper which focuses on the mathematical modeling of information flow. Following are several examples to show the complexity of perceived dissonance.

Indicated dissonance may not be perceived as dissonance if the human operator has a mental model that describes why indicated dissonance is present. In the case of GPWS and EGPWS, if EGPWS alerts without a GPWS alert, dissonance will not be perceived if the pilot understands that by design EGPWS should alert earlier than GPWS. On the other hand, if GPWS is at a higher alert stage than EGPWS, there may be perceived dissonance because the pilot may not understand why EGPWS does not rate the terrain as a threat while GPWS does.

Differences in system alert stage can be present without causing perceived dissonance if the two alerting systems have different roles. For example, EGPWS is designed to provide warning of terrain and TCAS is designed for other traffic. There is no perceived dissonance if TCAS gives an alert while GPWS is silent, although there is indicated dissonance since two systems are in different alert stages. There could be perceived dissonance if both TCAS and GPWS alert but TCAS commands a descent and GPWS commands a climb.

Given the wide variety of commands, there may be subtleties in the commands that affect whether certain differences are perceived to be dissonant or not. The general concept, however, is that the resolution trajectories implied by the command (whether implicit or explicit) should not be disjoint; otherwise, dissonance may be perceived. That is, perceived command dissonance could occur if no single action can satisfy both systems' commands. For example, consider two alerting systems where system 1 commands a climb while system 2 commands a right turn. One view could be that a climb is inconsistent with turning and so no single action could satisfy both commands. An alternate view could be that a climbing turn would satisfy both commands. Whether these commands are dissonant therefore, would require a more detailed study of the effects of the information on the operator. Still, the potential for dissonance could be identified by examining resolution commands, helping to focus future research on areas where problems may arise.

In some cases, indicated consonance may actually be perceived as dissonance. This may occur when the human operator is affected by other factors including the dynamics of the process, the nominal information, and the internal mental model of the situation. Consider two systems, where one system initially indicates no threat while the second system indicates a high degree of danger and a warning is issued. If the first system then upgrades the alert stage to a caution while the second system downgrades the alert stage, also to a caution, perceived dissonance may exist. Even though the two systems now agree about the proper alert stage (there is no indicated dissonance) the human may be uncertain as to whether the situation is improving or getting worse.

C. Major Causes of Indicated Dissonance

To be able to deal with dissonance schematically, we need to first identify when and where dissonance could happen; that is, to identify the major causes and conditions for dissonance.

Certainly, perceived dissonance is critically important. However, perceived dissonance is likely connected in some way to indicated dissonance. Thus, it is important to begin by identifying the root causes of indicated dissonance. Based on the general state-space representation of multiple alerting systems, two major causes of indicated dissonance can be identified: logic difference and sensor error.

Alerting systems map a set of measured or estimated states of a controlled process into discrete alert stages and discrete or continuous hazard resolution commands. So, if there is indicated dissonance between alert stages or resolution commands (output $\mathbf{a}_i$ or $\mathbf{c}_i$) between two alerting systems, it could be because of 1) a difference in alerting thresholds or resolution logic (T_i or R_i in Fig. 1) or 2) a difference in measured states ($\hat{\mathbf{y}}_i$ in Fig. 1) between the two alerting systems. Sensor systems, corrupted by noise $\mathbf{n}$, map the observable states $\mathbf{y}$ into the measured states $\hat{\mathbf{y}}$. A difference between measured states could arise due to random sensor error or due to differences in sensor coverage (the set of observable states for each alerting system).

IV. Dissonance Originating From Logic Differences

As identified in Section III, one of the major causes of dissonance may be a logic difference between two systems. When two systems are designed to protect against different hazards or when different time scales are used by two systems for the same hazard, threshold functions $T_{\rm i}$ and resolution logic $R_{\rm i}$ are usually different in order to satisfy different objectives. Thus, two systems may be in different alert stages or provide different resolution advisories for the same process state. In this section, we develop ways to identify the conditions in which the alert stages or resolution advisories produce dissonance.

A. Formal Description of Threshold Functions

To expose those conditions where dissonance may occur, we begin by examining the state space of the alerting system and observing when alerts are issued. The threshold functions for each alerting system, T_1 and T_2, and the resolution functions R_1 and R_2 map a given state of the process into a corresponding alert stage and a resolution command. These mappings are typically defined by a set of predicates (or inequality statements) based on certain parameter values. Each predicate evaluates to either true or false. One example predicate for collision alerting might be: "if the time to impact is less than p s, then use alert stage 1," where p is some parameter value. In general, there may be a set of such comparisons made between the states in $\mathbf{y}$ and a set of threshold parameters. To begin, we assume the alerting system uses the exact observable states; that is, no sensor error is considered.

Let the ith alerting system have a number of such predicates where the jth predicate is denoted $f_{\rm ij}$. Each predicate represents a boundary that divides the state space into a subset. Inside the subset, the predicate is true; outside, the predicate is false. Combinations of these subsets then form an *alert set* within the universe of the state space, $\mathbf{U}$. Each resulting alert set is denoted $A_{\rm ik}$ for the kth alert set of system i (Fig. 2) and represents a unique combination of alert stage and resolution command. It is then possible to map out what states in the space of $\mathbf{y}$ lead

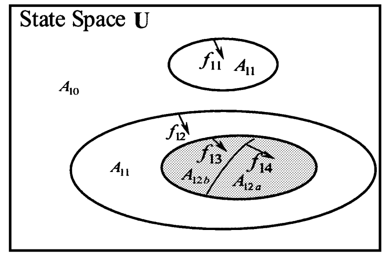

Fig. 2. Example predicates and alert sets.

to different alert sets. For example, in Fig. 2, alerting system 1 has four alert sets. A_{10} and A_{11} represent the sets of states in which system 1 is in alert stage 0 or 1, respectively. Note that there are two distinct regions in state space that each map into A_{11}; that is, there are two distinct situations which would produce a stage-1 alert from the system. Alert set $A_{\rm 12a}$ represents alert stage 2 with a climb command, while alert set $A_{\rm 12b}$ is alert stage 2 with a descend command. As shown, A_{11} is active when predicate f_{11} or f_{12} is true but f_{13} is false; $A_{\rm 12a}$ is active when predicates f_{13} and f_{14} are true, and $A_{\rm 12b}$ is active when predicate f_{13} is true but f_{14} is false.

Thus, the threshold functions of an alerting system can be formally described by their corresponding predicates. For example, the threshold function of system 1 in Fig. 2 can be formally described as,

$$T_1 = \begin{cases} f_{11},\ F_{11}(\mathbf{y}, \mathbf{p}_{11}) < 0 \\ f_{12},,\ F_{12}(\mathbf{y}, \mathbf{p}_{12}) < 0 \\ f_{13},\ F_{13}(\mathbf{y}, \mathbf{p}_{13}) < 0 \\ f_{14},\ F_{14}(\mathbf{y}, \mathbf{p}_{14}) < 0 \\ A_{12a} = f_{13} \cap f_{14} \\ A_{12b} = f_{13} \cap \bar{f}_{14} \\ A_{11} = \bar{f}_{13} \cap (f_{11} \cup f_{12}) \\ A_{10} = U - A_{11} - A_{12a} - A_{12b} \end{cases} \tag{7}$$

where the jth predicate $f_{\rm 1j}$ is described as an inequality statement of the observable state $\mathbf{y}$ and a set of parameters $\mathbf{p}_{\rm 1j}$.

As a more concrete example, in Part II we present a model for an in-trail spacing task in which the in-trail separation of two vehicles is monitored by two independent alerting systems. System 1 alerts ($\mathbf{a}_1 = 1$) when the range between vehicles (r) is greater than a threshold distance R_1. The threshold function is formally defined as

$$T_1 = \begin{cases} f_{11}\colon r > R_1 \\ A_{11} = f_{11} \\ A_{10} = \mathbf{U} - A_{11} \end{cases}. \tag{8}$$

System 2 alerts ($\mathbf{a}_2 = 1$) when the vehicles are converging and projected to be less than a range R_2 apart within τ seconds ($\dot{r} < 0$ & $(r - R_2)/-(\dot{r}) < \tau$), or if they are close together and diverging but at a slow rate ($r\dot{r} < H$, where H is some constant). The threshold function of system 2 is formally defined as

$$T_2 = \begin{cases} f_{21},\ \dot{r} < 0 \\ f_{22},\ \frac{r - R_2}{-\dot{r}} < \tau \\ f_{23},\ r\dot{r} < H \\ f_{24},\ r < R_2 \\ A_{21} = (f_{21} \cap f_{22}) \cup (f_{23} \cap f_{24}) \\ A_{20} = \mathbf{U} - A_{21} \end{cases}. \tag{9}$$

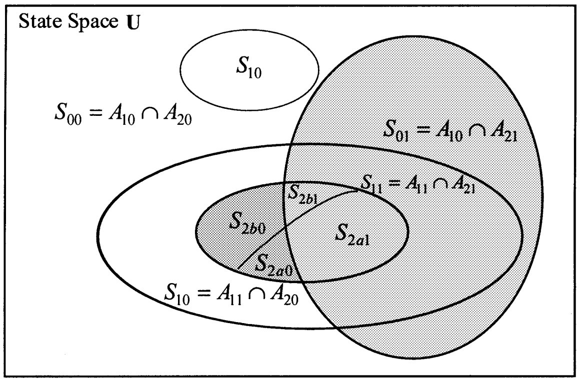

Fig. 3. Example combination of alert sets.

B. Identification of Conditions for Dissonance

When two systems operate simultaneously, combinations of alert sets may result in dissonance. The combinations of the alert sets of the two systems are given by the intersections of the A_{ik} sets. These intersection sets are denoted S_{mn} where m is the alert set from system 1 and n is the alert set from system 2.

$$S_{\mathrm{mn}} = A_{1m} \cap A_{2n}. \tag{10}$$

Continuing the example from Fig. 2, suppose a second alerting system, 2, has a threshold function formally described as

$$T_2 = \begin{cases} f_{21},\, F_{21}(\mathbf{y}, \mathbf{p}_{21}) < 0 \\ A_{21} = f_{21} \\ A_{20} = U - A_{21} \end{cases}. \tag{11}$$

Then there are nine combinations of the alert stages of the two alerting systems (Fig. 3). S_{11} in Fig. 3, for example, represents the set of states where both systems are in alert stage 1. $S_{2\mathrm{a}1}$ represents a condition where system 1 commands a climb while system 2 is in stage 1.

Next, human factors issues have to be considered by examining each set S_{mn} to determine if there is perceived dissonance in that situation. This human factors analysis is beyond the scope of this paper; we assume here that we are able to determine which regions S_{mn} are in fact perceived to be dissonant. The subset of space where perceived dissonance exists is then called dissonance space. Then, the conditions for dissonance are the conditions for those sets S_{mn} that have been determined to exhibit perceived dissonance. For example, if it was determined that a simultaneous climb command from system 1 was dissonant with alert stage 1 from system 2, the formal condition for dissonance could be described by

$$S_{2a1} = A_{12a} \cap A_{21} = f_{13} \cap f_{14} \cap f_{21}. \tag{12}$$

It is worth mentioning that the observable states are usually different for different alerting systems. Thus, the threshold functions for different alerting systems are usually described in different state spaces. To be able to identify the conditions for dissonance, we need to map the threshold functions of the different alerting systems into a single state space. For the example presented above, if the original threshold functions of alerting system 2 are described in state space $\mathbf{y}'$, that is, the predicate f_{21} is originally described as

$$F'_{21}(\mathbf{y}', \mathbf{p}'_{21}) < 0 \tag{13}$$

it needs to be mapped into

$$F_{21}(\mathbf{y}, \mathbf{p}_{21}) < 0 \tag{14}$$

which is in the same state space as alerting system 1, through a state space transformation. If two state spaces are orthogonal, then a simple union of state spaces can be used to identify the conditions for dissonance. For example, if the threshold functions of alerting system 1 are described in state space $\mathbf{y}_1$ while system 2 is in state space $\mathbf{y}_2$, and $\mathbf{y}_1$ and $\mathbf{y}_2$ are orthogonal, then the formal descriptions of both systems' threshold functions need to be presented in state space $\mathbf{y} = \mathbf{y}_1 + \mathbf{y}_2$

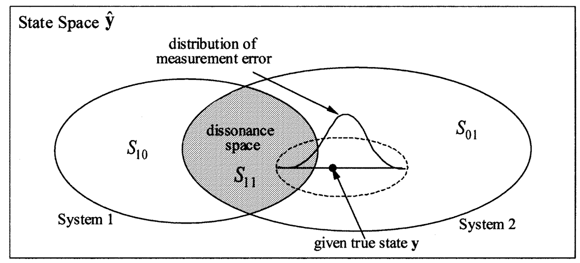

Fig. 4. Measurement error effects on dissonance.

V. Dissonance Originating From Sensor Error

Given a true state that is outside the dissonance space defined by a logic difference, the measurement of that state given by two systems could still trigger dissonance with some probability because of measurement error.

For example, in Fig. 4, suppose the dissonance space is S_{11}, where both alerting systems alert but present dissonant resolution advisories. The given true state $\mathbf{y}$ is in space S_{01}, which is outside the dissonance space S_{11}. With sensor error, the measurement obtained by system 1 may still trigger an alert placing $\hat{\mathbf{y}}_1$ inside its alert threshold boundary, and the measurement obtained by system 2 may trigger an alert if $\hat{\mathbf{y}}_2$ is inside its alert threshold boundary. Thus, a state outside dissonance space may still trigger dissonance.

As discussed in Section II, the measured state available to an alerting system is given by $\hat{\mathbf{y}}_i = \mathbf{y} + \mathbf{n}_i$. Given the probability density function (PDF) of the measurement noise for each alerting system $\mathbf{f}_{\mathbf{n}_i}$; the PDF $\mathbf{f}_{\hat{\mathbf{y}}_i \mid \mathbf{y}}(\hat{\mathbf{y}}_i \mid \mathbf{y})$, describing the measured state, is given as

$$\mathbf{f}_{\hat{\mathbf{y}}_i \mid \mathbf{y}}(\hat{\mathbf{y}}_i \mid \mathbf{y}) = \int_{-\infty}^{+\infty} \mathbf{f}_{\mathbf{y}}(\mathbf{y}) \mathbf{f}_{\mathbf{n}_i}(\hat{\mathbf{y}}_i - \mathbf{y}) \mathbf{d}\hat{\mathbf{y}}_i = \mathbf{f}_{\mathbf{n}_i}(\hat{\mathbf{y}}_i - \mathbf{y}). \tag{15}$$

Then the probability of system 1 alerting for a state $\mathbf{y}$ in the example described above can be given as

$$P_{11} = P(\text{System 1 Alert} \mid \mathbf{y}) = \int_{\hat{\mathbf{y}}_1 \in A_{11}} \mathbf{f}_{\hat{\mathbf{y}}_1 \mid \mathbf{y}}(\hat{\mathbf{y}}_1 | \mathbf{y})\, \mathbf{d}\hat{\mathbf{y}}_1. \tag{16}$$

And the probability of system 2 alerting is

$$P_{21} = P(\text{System 2 Alert} \,|\, \mathbf{y}) = \int_{\hat{\mathbf{y}}_2 \in A_{21}} \mathbf{f}_{\hat{\mathbf{y}}_2 \,|\, \mathbf{y}}(\hat{\mathbf{y}}_2 \,|\, \mathbf{y})\, \mathbf{d}\hat{\mathbf{y}}_2. \tag{17}$$

Then if the measurements from two systems are independent, the probability of dissonance is

$$P(D|\mathbf{y}) = P(S_{11} \,|\, \mathbf{y}) = P_{11} \times P_{21}. \tag{18}$$

If the measurements from the two systems are correlated, a Monte Carlo simulation can be executed, for example, to obtain the probability of dissonance. Also note that (16) and (17) could be extended to multidimensional PDFs.

With measurement noise, it is possible that the measured state triggers dissonance although the true state is not in the dissonance space (false dissonance); or the measured state may not trigger dissonance even though the true state is in dissonance space (missed dissonance). Given a true state and the PDF $\mathbf{f}_{\hat{\mathbf{y}}_i \,|\, \mathbf{y}}(\hat{\mathbf{y}}_i \,|\, \mathbf{y})$ for both systems, we can obtain the probability of false dissonance and missed dissonance.

As discussed earlier, for the same example shown in Fig. 4, given a state that is outside the dissonance space S_{11}, false dissonance occurs if each measured state triggers each system's alert. That is, the probability of false dissonance is

$$\begin{aligned} P(\mathrm{FalseDissonance} \,|\, \mathbf{y} \notin S_{11}) &= P(S_{11} \,|\, \mathbf{y} \notin S_{11}) \\ &= P_{11} \times P_{21}. \end{aligned} \tag{19}$$

Given a state $\mathbf{y}$ which is inside the dissonance space S_{11}, missed dissonance occurs when one or both of the two alerting systems misses detecting the hazard. That is, the probability of missed dissonance is

$$\begin{aligned} &P(\text{MissedDissonance} \,|\, \mathbf{y} \in S_{11}) \\ &\quad = P(S_{10} \,|\, \mathbf{y} \in S_{11}) + P(S_{01} \,|\, \mathbf{y} \in S_{11}) \\ &\qquad + P(S_{00} \,|\, \mathbf{y} \in S_{11}) \\ &\quad = P_{10} \times P_{21} + P_{11} \times P_{20} + P_{10} \times P_{20}. \end{aligned} \tag{20}$$

Where P_{10} is the probability of no system 1 alert

$$\begin{aligned} P_{10} &= P(\text{No System 1 Alert} \,|\, \mathbf{y} \in S_{11}) \\ &= \int_{\hat{\mathbf{y}}_1 \in A_{10}} \mathbf{f}_{\hat{\mathbf{y}}_1 \,|\, \mathbf{y}}(\hat{\mathbf{y}}_1 \,|\, \mathbf{y})\, \mathbf{d}\hat{\mathbf{y}}_1. \end{aligned} \tag{21}$$

And P_{20} is the probability of no system 2 alert

$$\begin{aligned} P_{20} &= P(\mathrm{NoSystem2Alert} \,|\, \mathbf{y} \in S_{11}) \\ &= \int_{\hat{\mathbf{y}}_2 \in A_{20}} \mathbf{f}_{\hat{\mathbf{y}}_2 \,|\, \mathbf{y}}(\hat{\mathbf{y}}_2 \,|\, \mathbf{y})\, \mathbf{d}\hat{\mathbf{y}}_2. \end{aligned} \tag{22}$$

To provide a more comprehensive view of sensor error, we translate the sensor error into a redistribution of the threshold functions of each alerting system. Since the threshold function is a function of $\hat{\mathbf{y}}$, the threshold boundaries are themselves functions of random variables. That is

$$\mathbf{a} = T(\hat{\mathbf{y}}) = T(\mathbf{y} + \mathbf{n}). \tag{23}$$

The distributions of threshold functions for each alerting system can be determined through algebraic operations on random variables.

For example, in Fig. 5, the solid oval line is the original threshold boundary. That is, if the measured state $\hat{\mathbf{y}}$ is inside the boundary, the system will give an alert. Given the sensor error distribution, the threshold boundary in terms of $\mathbf{y}$ are the dashed lines, between which the measured state will trigger system alert with some probability. The alerting space has been enlarged to the outer dashed line because of false alarms introduced by sensor error, and those states inside the original threshold function now have some nonzero probability of missed detection.

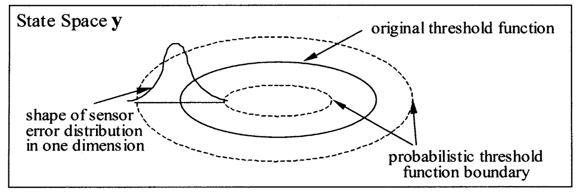

Fig. 5. Translating sensor error into a threshold boundary change.

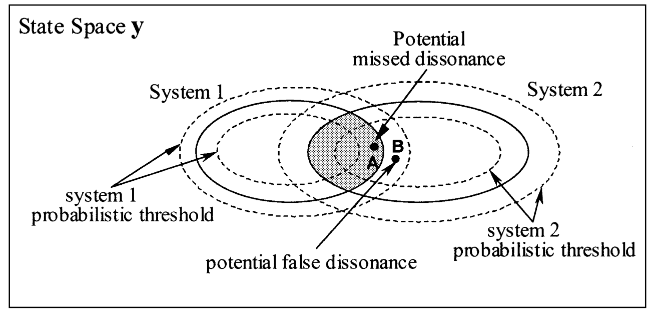

Fig. 6. Change in dissonance space due to sensor errors.

Now, using the same example as in Fig. 4 with S_{11} as dissonance space, we can consider the threshold change after introducing the sensor error and analyze the redistribution of dissonance space (Fig. 6).

In Fig. 6, dissonance space is now probabilistic. For example, point B in Fig. 6 is outside the original dissonance space, but it could trigger dissonance with some probability because of sensor error (false dissonance). Similarly, point A in Fig. 6 is inside the original dissonance space, but it may not trigger dissonance because of sensor error (missed dissonance).

Given a requirement for a certain probability of dissonance, new alert stage boundaries can be determined, and then the same analysis method as that for dissonance due to logic differences can be used.

A. Example Analysis of the Contribution of Sensor Error

Since dissonance can be generated from two different sources, logic differences or sensor error, it would be beneficial to identify the relative contribution of each source. This can be used to help the designer apply the best method to mitigate dissonance (such as using a more accurate sensor or modifying the design of the alerting logic). Knowing the probability of dissonance for each state in the design space would help the designer reshape the threshold functions for each alerting system.

In this section, we give an example analysis of the probability of dissonance, identify the contribution of sensor error to dissonance for a set of uncertain trajectories, and compare it with the contribution of logic differences. At this point, it is assumed that each alerting system is affected independently by noise.

Let P_{1m} denote the probability that system 1 is in alert set m, P_{2n} the probability that system 2 is in alert set n, and D be the event of dissonance. For a given true state $\mathbf{y}$, if the dissonance space is S_{mn}, and if the measurements from two systems are independent, then the probability of dissonance for the given state $\mathbf{y}$ is

$$P(D \mid \mathbf{y}) = P_{1m} \times P_{2n}. \tag{24}$$

Probabilities P_{1m} and P_{2n} can be obtained analytically or through simulation as discussed in the previous section.

If an entire trajectory is expected to be followed, the designer may want to know the cumulative probability of dissonance occurring up to some point along the trajectory. Consider a given state trajectory T. We define the cumulative probability of dissonance up to time t along the trajectory as

$$P_c(D \mid T(t)) = 1 - \prod_{t=0}^{t} (1 - P(D \mid \mathbf{y}(t))) \tag{25}$$

where $\prod_{t=0}^{t} (1 - P(D \mid \mathbf{y}(t)))$ is the probability of no dissonance up to time t. As time goes to infinity, we have the cumulative probability of dissonance over the entire trajectory T

$$P_\infty(D \mid T) = \lim_{t\to\infty} P_c(D \mid T(t)). \tag{26}$$

This value is the probability of dissonance occurring somewhere along the trajectory.

In most cases, we don't know exactly which trajectory will be followed. Based on experience or after running simulations, we may be able to determine the probability distribution of a set of r different uncertain trajectories $P(T_i)$. From this, we can get an overall cumulative probability of dissonance for a set of uncertain trajectories

$$P_\infty(D) = \sum_{i=1}^{r} P_\infty(D \mid T_i) \times P(T_i). \tag{27}$$

This value is the probability of getting a dissonant situation in the future, given a starting point.

After defining the probability of dissonance, we can analyze the effect of sensor accuracy on the probability of dissonance. Consider a set of possible trajectories without any noise. We use P' to denote probabilities in ideal conditions without any noise. This set of trajectories can be separated into two subsets. Subset A includes those trajectories in which there are states in the dissonance space, that is, $P'_\infty(D \mid T_i) = 1$. Subset B includes those trajectories in which there is no state in dissonance space, that is, $P'_\infty(D \mid T_i) = 0$. Due to logic differences alone, the overall cumulative probability of dissonance for a set of uncertain trajectories is then

$$P'_\infty(D) = \sum_{i=1}^{r} P'_\infty(D \mid T_i) \times P(T_i). \tag{28}$$

From this, the contribution of sensor error to dissonance $P_\infty(D)$ can be compared to the contribution of logic difference to dissonance $P'_\infty(D)$. Now, considering sensor accuracy, we can define the probability of false dissonance as the probability of dissonance triggered by those trajectories in subset B, on which there is no true state in the dissonance space contributed by logic difference. That is

$$P_{\mathrm{FD}} = \sum_{T_i \in B} P(T_i) \times P_\infty(D \mid T_i). \tag{29}$$

And the probability of missed dissonance is defined as the probability of dissonance missed by those trajectories in subset A, on which there are true states in the dissonance space contributed by logic difference, that is

$$\begin{aligned} P_{\mathrm{MD}} &= \sum_{T_i \in A} P(T_i) \times P_\infty(\bar{D} \mid T_i) \\ &= \sum_{T_i \in A} P(T_i) \times (1 - P_\infty(D \mid T_i)) \end{aligned} \tag{30}$$

where $\bar{D}$ means no dissonance. So, the total probability of dissonance with sensor error would be

$$P_\infty(D) = P'_\infty(D) + P_{\mathrm{FD}} - P_{\mathrm{MD}} = \sum_i P(T_i) \times P_\infty(D \mid T_i). \tag{31}$$

Typically, sensor error would increase the overall probability of dissonance. However, when $P_{\mathrm{FD}} < P_{\mathrm{MD}}, P_\infty(D) < P'_\infty(D)$, and sensor error may actually provide some benefit, decreasing the overall probability of dissonance. This may not be beneficial overall, though. Decreased overall cumulative probability of dissonance means a larger probability of missed dissonance, which also means that one of the alerting systems may have missed detection of the hazard. The hazard may not be able to be avoided because of this missed detection.

VI. Concluding Remarks

Alerting system dissonance has not been a major concern in the past beyond the desire to minimize simultaneous alerts and prevent information overload. At least one accident and other incidents have occurred, however, in part due to alerting conflicts. Conflicting alert information is likely to become even more prevalent as alerting systems continue to be injected into complex systems operations. Several areas in aerospace have already been identified where dissonance is likely to occur if this issue is ignored, and certainly there are other regimes where similar problems are of concern.

To date, management of dissonance between systems has mainly involved inhibition of alerts, and has typically occurred without a structured understanding of the specific issues involved. This paper presents a more formal model that has three objectives. First, it aids in understanding the different types of dissonance that may occur. This will be useful in building a common terminology with which to compare and discuss alerting system conflicts. Second, the model can be used to identify when or where each different type of dissonance could occur in a given operation. Third, the model may be used to design and evaluate more advanced mitigation contingencies to prevent or impede dissonance from occurring, which is the major topic of the companion paper (Part II).

The model is based on a state-space representation of alerting system operation. This provides a generic framework that facilitates articulating the specific information elements that are sensed, processed, and displayed by an alerting system. By drawing the mapping between process states and the resulting alert stages and resolution commands, it is then possible to identify conditions that lead to dissonance. The model of alert dissonance developed was applied to identify dissonance between systems such as TCAS and the recently-proposed airborne conflict management (ACM) in [17], which focused on dissonance due to logic differences.

The critical limitation of the model presented here is that it relies heavily on human factors studies to determine what conditions are actually dissonant. Our model facilitates uncovering where different types of indicated dissonance may occur, but does not by itself provide guidance as to which regions of indicated dissonance actually cause human factors problems. Accordingly, more effort into the human factors issues behind dissonance is clearly necessary.

Because of its generalized nature, the methodology developed in this paper can be applied to model and analyze the interactions between any decision support systems. Advanced decision support systems that are currently under consideration in the aerospace industry would benefit from this work. For example, the Center TRACON Automation System (CTAS) [18], which is being developed at the NASA Ames Research Center, generates air traffic advisories designed to increase fuel efficiency, reduce delays, and provide automation assistance to air traffic controllers. CTAS itself includes several automation functions, all of which must be well integrated not only within CTAS itself, but also with other ground-based systems (i.e., User Requested Evaluation Tool (URET) developed by MITRE Corp. [19]) and airborne systems (TCAS, ACM, etc.). The methodology in this paper can be applied to determine interaction issues among automation functions within CTAS, between CTAS and other ground-based systems, and between CTAS and airborne decision support systems.

To avoid or mitigate dissonance, a hybrid model is presented in the companion paper (Part II) to describe the dynamics of the hybrid process incorporating multiple alerting systems. This approach facilitates designing countermeasures to reduce the likelihood of dissonance or at least to reduce the negative effects of dissonance on the process.

References

[1] A. Pritchett, B. Vandor, and K. Edwards, "Testing and implementing cockpit alerting systems," *Reliab. Eng. Syst. Saf.*, vol. 75, no. 2, pp. 193–206, Feb. 2002.

[2] A. R. Pritchett and R. J. Hansman, "Pilot Non-Conformance to Alerting System Commands During Closely Spaced Parallel Approaches," MIT Aeronautical Systems Lab. Rep., ASL-97-2, Cambridge, MA, Jan. 1997.

[3] Aviation Safety Network, Accident Description (2002, July 1). [Online]. Available: http://aviation-safety.net/database/2002/020 701-1.htm

[4] J. Veitengruber, G. Boucek, and W. Smith, "Aircraft Alerting Systems Criteria Study, Vol. 1: Collation and Analysis of Aircraft Alerting Systems Data," National Tech. Inform. Service, Springfield, VA, FAA-RD-76-222, May 1977.

[5] "Application of Airborne Conflict Management: Detection, Prevention, and Resolution," Radio Technical Committee Aeronautics (RTCA), Washington, DC, Doc. RTCA/DO-263, Dec. 2000.

[6] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Hum. Factors*, vol. 37, no. 1, pp. 32–64, 1995.

[7] T. B. Sheridan, *Telerobotics, Automation, and Human Supervisory Control*. Cambridge, MA: MIT Press, 1992.

[8] C. D. Wickens, *Engineering Psychology and Human Performance*. New York: Harper Collins, 1992.

[9] N. Sarter and D. Woods, "How in the world did we ever get into that mode? Mode error and awareness in supervisory control," *Hum. Factors*, vol. 37, no. 1, pp. 5–19, 1995.

[10] R. D. Sorkin and D. D. Woods, "Systems with human monitors: A signal detection analysis," *Hum. Comput. Interaction*, vol. 1, pp. 49–75, 1985.

[11] "Minimum Performance Specifications for TCAS Airborne Equip.," Radio Technical Committee Aeronautics (RTCA), Washington, DC, Doc. RTCA/DO-185, Sept. 1983.

[12] J. L. DeCelles, *The Delayed GPWS Response Syndrome*. Herndon, VA: Aviation Research Education Foundation, July 1991.

[13] J. Lee and N. Moray, "Trust, control strategies and allocation of function in human-machine systems," *Ergonomics*, vol. 35, pp. 1243–1270, 1992.

[14] J. D. Lee and N. Moray, "Trust, self-confidence, and operator's adaptation to automation," *Int. J. Hum. Comput. Studies*, vol. 40, pp. 153–184, 1994.

[15] R. Parasuraman and V. A. Riley, "Humans and automation: Use, misuse, disuse, abuse," *Hum. Factors*, vol. 39, pp. 230–253, 1997.

[16] V. Riley, *Operator Reliance on Automation: Theory and Data*. Hillsdale, NJ: Lawrence Erlbaum, 1996.

[17] L. Song and J. K. Kuchar, "Modeling and analysis of conflicts between alerting systems," presented at the AIAA Guidance, Navigation, and Control Conference, Montreal, Canada, Aug. 6–9, 2001.

[18] D. R. Isaacson and H. Erzberger, "Design of a conflict detection algorithm for the center/TRACON automation system," presented at the Proc. Digital Avionics Systems Conf., 16th DASC, AIAA/IEEE, vol. 2, 1997.

[19] H. Erzberger, R. A. Paielli, D. R. Isaacson, and M. M. Eshow, "Conflict detection and resolution in the presence of prediction error," presented at the Proc. 1st USA/Europe Air Traffic Management R&D Seminar, Saclay, France, June 17–20, 1997.

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