JDL Level 5 Fusion Model "User Refinement" Issues and Applications in Group Tracking

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ABSTRACT

The 1999 Joint Director of Labs (JDL) revised model incorporates five levels for fusion methodologies including level 0 for preprocessing, level 1 for object refinement, level 2 for situation refinement, level 3 for threat refinement, and level 4 for process refinement. The model was developed to define the fusion process. However, the model is only for automatic processing of a machine and does not account for human processing. Typically, a fusion architecture supports a user and thus, we propose a **Level 5 "User refinement"** to delineate the human from the machine in the process refinement. Typical "human in the loop" models do not deal with a machine fusion process, but only present the information to the human on a display. We seek to address issues for designing a fusion system which supports a user: trust, workload, attention and situation awareness. In this paper, we overview the need for a Level 5, the issues concerning the human for realizable fusion architectures, and examples where the human is instrumental in the fusion process such as group tracking.

Keywords: Information Fusion, Group Tracking, Identity, workload, attention, situation awareness, trust, HMI, HCI

1. INTRODUCTION

The fusion and tracking community has developed refined mathematical algorithms from which to track targets based on sensed positional measurement information [1]. Human visual tracking [2] incorporates the inherent process of motion detection and subsequently sequencing measurement information. The integration of these methods is the fusion of the human motion processing of observed target identity (ID) and mathematical-machine positional information[3]. Tracking ultimately is performed for human needs, whether it be for surveillance applications or object assessment (i.e. air traffic control). Industrial systems have sometimes employed fusion technology, however, the goal was to present target localization as opposed to developing a strategy for man-machine fusion-tracking interactions. Limited research has been performed in the area of incorporating a human into the standard fusion models. Here, we see the human as an active component in the fusion process to optimize sensors to best locate and ID targets.

There are many sensor fusion architectures and some have evolved with time. Machines are quick at data processing and it is time for higher level fusion issues to be addressed to incorporate the human in the loop. We are interested in breaking up the high-level sensor management task into two areas – one for the computer and one for the human. The human is interested in many aspects that can not be programmed into the computer – such as online strategies dealing with measurement process uncertainties and wide area surveillance. Humans are excellent in monitoring and controlling the fusion process. In the future, one could argue that the human and the fusion system might be able to interact in an adaptive way, however a new fusion paradigm would be needed to leverage the human's intelligent reasoning skills [3]. The human brain, with the prefrontal cortex performing higher level reasoning and attentional functions, can work to control the fusion process to insure that the correct associations are performed by the machine.

Section 2 overviews fusion and user models for human-machine interaction (HMI). Section 3 overviews the JDL-user model that incorporates Level 5 User Refinement. Section 4 addresses issues of situation awareness, attention, workload, and trust needed in Level 5. Section 5 presents simulated results. Section 6 draws conclusions and ongoing efforts.

2. HUMAN-MACHINE FUSION

Information fusion exists in many forms, such as integrating audio and visual data, plans, or surveillance requirements. It is important to remember that the goal of any model is to extend the sensing capabilities of the human to prosecute his or her environment. To effectively input, fuse, and output actions, models help to illustrate these functions.

2.1 Information Fusion Models

Two models that are fusion-focused are the Data-Feature-Decision (DFD) [4] model and the traditional Joint Director's of Labs (JDL) model [5], shown in Figure 1 and Figure 2 respectively. Dasarathy introduced the DFD model to guide a

machine to make decisions based on the data. The JDL model consists of five modules with a human computer interface. While the model has been the standard for military research and fusion discussion, it needs to be adapted to reflect the importance of the human for information exploitation. The exploitation of information includes control, decision, and action. In the revised JDL model, it can be stated that the Level 4 process refinement might include both the user and sensor control functions as feedback for refining the fusion process.



Figure 1. DDF Model.

The Ominbus model [4], shown in Figure 3, is an extension of the OODA control loop (sometimes referred to as the Boyd control loop) as shown in Figure 4. In the case of the OODA and the Omnibus model, the machine is central to the model and is based on a human reasoning strategy.

2.2. User Models

The Human in the Loop

(HIL) of a semi-automated system must be given adequate situation awareness (SA). According to a pioneer and continued leader in the SA literature, Endsley stated that "Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." [6, 7, 8]. This now-classic model translates into 3 levels:

- Level 1 SA Perception of elements in the environment.
- Level 2 SA Comprehension of the current situation
- Level 3 SA Projection of future states

Operators of dynamic systems use their situation awareness in determining their actions. To optimize decision making, the SA provided by a system should be as precise as possible as to the objects in the environment (Level 1 SA). A situation awareness

approach should present a fused representation of the data (Level 2 SA) and provide support for the operator's projection needs (Level 3 SA) in order to facilitate operator's goals. From the SA model presented in Figure 5, workload is a key component of the model that affects not only SA, but also the decision and the action of the user.



and Objectives

Hard Decision Fusion

Figure 3. Omnibus Model.



JDL Model Revised

Level 2 SITUATION

Support DataBase

Figure 2. JDL Revised Model.

DataBase Management

Syster

Refine

Distributed

Human

Computer Interface

Information

Sources

Act

Doctrine

Rules and

Procedures

Level 3 THREAT

Refinemer

Fusior

DataBa

Level 0

Level 1 OBJECT

Refin

Level 4 PROCESS

Refinemer

Sensor/Info

Manager

of Actio Level 2 Level 3

Figure 5. Endsley's Situation Awareness Model

Individual

ity, Exper Training

Decide

Orient

Figure 4. OODA Loop.

Omnibus Model

Decision Making

Context Processing

Decide



Soft Decision Fusion

Pattern Processing

Research areas concerned with SA include 1) Military (e.g., UAVs, UCAVs, UGVs), 2) Aviation (ATC, Pilots), 3) Civil – Fire, Weather Surveillance, Decision Aiding, Response, 4) Medicine – Diagnosis, Surgery, Prostheses, 5) Industrial – Training, Repairs, 6) Educational – Distance Education, Disability Support, and 7) Robotics. SA is based on two perspectives: a) micro, which can be individual or tactical, and b) macro, which can be theater or strategic. Both levels of Situation Awareness are critical in the design and process of achieving Level 5 User Refinement capabilities in systems where the supervisory control by a HIL needs to facilitate decision making. [9] Fusion models must incorporate Workload, Attention, and Trust to aid SA in research, design and implementation.

2.3 User Designed Fusion Models

Two of the current user fusion models are the perceptual and the Neurophysiology models. An example of the perceptual reasoning machine (PRM) by Kadar [10] is shown in Figure 6. The model incorporates the prior information that the user has to help guide the prediction of the system. Current human knowledge can estimate the situation. Kadar uses the model to address the information gathering for actions pertinent to the user.

While perception is a psychological construct, we can also address the user needs by addressing the biology of the human in the fusion process. Human fusion of several sensor modalities is expressed in the Neurophysiological Information Fusion (NIF) architecture. The sensor modalities considered include visual, auditory, and somatosensory to locate a target. The visual system







is composed of the eyes, the thalamic, the superior colliculus, and the primary visual cortex. When a person is "searching"

a region of space, he is looking for objects or events. To anticipate the location of the object, the person predicts what the target looks like and maps that image prediction onto a consistent, stable model of his environment. After an object is *detected*, (i.e. listening for a threat warning) a cue guides a person to look for the target amongst objects in the common operation picture (COP). The auditory system can cue the visual system to the general target location, but where and when should the visual system start looking? A higher-level cognitive function of extraction is needed to associate information. Using a feature-based extraction approach from the cued visual image is essential to the model. To further combine biological, perceptual, and machine-fusion, we explore elements of "User Refinement".



Figure 7. Neurophysiological Information Fusion (NIF)

3. THE JDL-U SENSOR FUSION MODEL

The JDL-U model activities are:

<u>Level 0 – Sub-Object Data Assessment</u>: estimation and prediction of signal/object observable states on the basis of pixel/signal level data association (e.g. information systems collections);

<u>Level 2 – Situation Assessment:</u> estimation and prediction of relations among entities, to include force structure and force relations, communications, etc. (e.g. information processing, FDP, FL);

<u>Level 1 – Object Assessment:</u> estimation and prediction of entity states on the basis of observation-to-track association, continuous state estimation and discrete state estimation (e.g. data processing);

- <u>Level 3 Impact Assessment:</u> estimation and prediction of effects on situations of planned or estimated actions by the participants; to include interactions between action plans of multiple players (e.g. assessing threat actions to planned actions and mission requirements, DM, PE);
- <u>Level 4 Process Refinement</u> (an element of Resource Management): adaptive data acquisition and processing to support mission objectives (e.g. sensor management and information systems dissemination, IO, C^2).
- Level 5 User Refinement (an element of Knowledge Management): adaptive determination of who queries information and who has access to information. (e.g. information operations) and adaptive data retrieved and displayed to support cognitive decision making and actions (e.g. altering the sensor display).

The key to the fusion process is data association. Difficulties of using data association fusion are that: sensor data can be unreliable, the transfer process may corrupt data, or inappropriate information fusion actions may occur. By assessing the data (level 0 - 1) with information (level 2 and 3), sensor management

and user refinement (level 4 and 5) can correct for these fusion errors.

Process refinement controls information flow. User refinement guides data collection, region of coverage, situation and threat assessment as well as process refinement of sensor selections. While each level needs fused information from lower levels, the refinement of fused information is a function of the user. Two important issues are *control* of the information and the *planning* of actions. There are many issues related to centralized and distributed control such as team management and individual survivability. For example, an Army Tactical Operational Center (TOC) display, shown in Figure 9, might be globally distributed, but centralized for a single commander for local operations. [see 11 for another example]. Thus, the information received from lower levels, but also afford analysis and distribution of commander actions, directives, and missions. Once actions are taken, new observable data should be presented as a operational feedback information. Likewise, the analysis should include the local and global operational changes and the

confidence of new information. Finally, execution should include updates to the distributed system of orders, plans, and actions to people carrying out mission directives. Thus, Level 4, it is not the fusing of signature, image, and track intelligence data, but that of fusion of decision intelligence (DECINT) information for functionality.

DECINT information is a globally and locally refined assessment of fused observational information. DECINT is the information for which a user can act on. Additionally, HUMINT data can be gathered from other people to determine what information to collect, analyze, and distribute to others. One way to facilitate the receiving, analyzing, and distribution of actions is that of the observe, orient, decide, and act (OODA) loop. The OODA loop requires the display of information for functional cognitive decision-making. In this case, the display of information should orient a person as in determining the situation based on the observed information (i.e. situation assessment). These actions need to be assessed from the user ability to deploy his resources against the resources, constraints, and opportunities of the environment.

The processing of information can be labeled as *action intelligence* (ACTINT) information because an assessment of possible/plausible actions needs to be considered. Thus, the goal of any fusion system is to provide the user a set of refined information for functional action. Taken together, the fusion system is actually a *functional sensor* for the user, whereas the traditional fusion models are just an observational sensor. The user refinement block not only is the determination of *who*

Figure 8. JDL-User Model



Figure 9. Tactical Operation Center.



wants the information and if they can refine the information, but *how* they process the information. Bottom-up processing of information can take the form of physical sensed quantities that support the higher-level functions. To include the automation as well as the user, it is important to view the user through an interface which the user can interact with the system (i.e. sensors). In this case, the user can query necessary information to make a decision while the automated system can work in the background to update the changing environment. Additionally, the functional fusion system is concerned with the entire situation while a user is typically interested in only a subsection of the environment. The computer has to try many combinations, but the human is adapt to locating the objects using sensor fusion.

Target ID and localization information is the desired result of either real or perceived data from a time and space representation. The difficulty with presenting the complete set of real data is the shear amount available. For example, A person monitoring many region of interest (ROI)s, waits for some event or *threat* to come into the sensor domain. In continuous collection modes, most sensor data is entirely useless. Useful data occurs when a sensed *event* interrupts the monitoring system and initiates a threat update. Decision-makers only need a subset of the entire data to perform successful SA and impact assessment. More importantly the user needs a time-event update on the target of interest. Thus, data reduction must be performed. The advantage of reducing the incoming data can especially be realized by using a fusion strategy over time as well as space. Target data can be fused into a single COP for enhanced SA.

An inherent difficulty resides in the fusion of only two forms of data. If one sensor perceives the correct target and the other does not, there is a *conflict*. Sensor conflicts increase the cognitive workload that must be reduced. However, if time, space, and spectral event fusion from different sensors, conflicts can be resolved within an emergent process to allow for better decisions over time. The strategy is to employ multiple sensors from multiple perspectives as shown in the proposed NIF model which characterizes the Level 5 user refinement system in the JDL-U model. Additionally, the HCI can be used to give the user a global and local SA to guide attention and reduce workload.

4. LEVEL 5 – USER REFINEMENT ISSUES

4.1 Workload

Muir and Moray, 1996 [12], observed that "A need to understand the interaction between human operators and automation has been created by the arrival of complex, dynamic, intelligent automation." Workload of the User was a different issue in automated systems, and not well described or measured. Endsley and colleagues present novel taxonomies and review the literature for Levels of Automation (LOA). [13] When considering workload components and impacts upon outcome in semi-automated systems, the appropriate LOA for the mission of the system must be experimentally researched and subsequently designed into the HIL system. LOA run the gamut, regardless of which LOA model is adopted, from manual (human) control to fully automated (no HIL) systems.

Workload measures and analysis becomes critically important as it is a confounder in the relationships of the other attention factors upon human performance. Current widely used workload measures in military, especially flight, applications include the objective SAGAT battery [6, 8] and both the SART inventory [14] or the NASA-TLX (Task Load Index) [15] for subjective measures of workload. Training, or the novice or expert status of the HIL with respect to the automation, must be

taken into account, as it affects objective and subjective measures of workload. Subjective measures of workload are strongly correlated with perceived success of decision making.

4.2 Attention

Any consideration of Level 5 User Refinement must incorporate known human factors of attention and workload upon SA and decision making. Elements of attention which are relevant include multimodal informational inputs. Primary modalities are visual and auditory systems, but tactile/haptic sensory channels are gaining research and design focus. Endsley [16] outlines key factors impinging upon attention include

- syntax, semantics, and clutter of presented information from prior system Levels,
- novice vs. expert status with the system,
- visual search strategies, auditory identification strategies, and
- training with respect to efficiency and efficacy of strategies



Figure 10. Endsley's Attention Model.

Theories of attention modeling that are relevant for SA include mental modeling and situational modeling, as shown in Figure 10. Mental modeling addresses the memory available to the human and processes for employing it. Typically, three forms of memory are discussed: short, working, and long-term memory. Since the human can only process a subset of the information available (i.e. 7 items at a time), the presentation of information to the human has to account for the amount that can be processed by working memory, and what types of search, salience recognition, and processing strategies are involved in the mission. Endsley outlines a key long-term memory construct [16] which includes (a) **episodic memory**, pertaining to object-time-location data from self-referent episodes (b) **semantic networks**, pertaining to the conceptual meaning of data and the relationship links or rules that the user accords the data, and (c) **schema**, which more broadly encompasses general knowledge, organized into structures like frames, plans, or scripts. [17]

Another construct of memory Endsley outlines [16] delineates mental vs. situational models. A mental model [18] is a mechanism whereby humans generate descriptions of purpose, explanations of system functions from observed system states, and predictions of future states. Another way to describe mental models is a complex schema that are plans of actions. A situational model [19] is a schemata depicting the current state of the system model Rasmussen [20] describes a situational model as a world model in his skills, rules, and knowledge model. A model of the current situation model can be viewed as a schema in memory that activates associated goals or scripts. Endsley notes that schema and mental models are developed with experience for a given environment and task. Initially, a human is a novice having only a vague idea of system components and rough heuristics to employ. With experience, recurrent situational components, associations, and causal relationships will develop such that a person becomes an expert.

These cognitive models are a critical starting point for the automation designer in overcoming working memory limitations by utilizing strengths in long term memory to assist short-term tasks and multi-modal search strategies. The next important point for automation designers are the classic theories of **attention**, especially in the visual domain. Five key theories can be summarized as follows [21 - 24]:

- Early Selection Theory (or Broadbent's Filter Theory) Early filtering of stimuli, generally by physical dimensions of signal input, results in one component 'message' being selected and propagated to downstream processing for efficiency. Other 'messages' are lost in this early filter. Efficiency takes priority over validity and mitigating error.
- Attenuation Theory 'Messages' are weighted with priority given to one message over the others; the former receives full processing (if this can be defined and analyzed) while latter receive only partial processing.
- Late Selection Theory Efficiency is sacrificed for validity and reduced error: All 'messages', attended or not, undergo semantic analysis and receive downstream processing, after which the key 'message' is determined since only one response can be made.
- **Object Based Theory** Rather than relying on physical parameters of input, a visual scene is dissected into distinct perceptual 'objects'. Leaving aside the selection of the salient 'message', the focus here is upon implications of how the scene is processed: parallel processing is theorized for object features while serial processing is theorized between objects. This theory informs research on guided search strategies within a field of view or a display.
- **Space-based theory-** Again leaving aside the selection of the salient information or 'message' of input data, the "spotlight" approach concerns the narrow field of view upon a scene, within which the visual attention is focused. *Parallel search* (at the same time) might be a target and location whereas *serially* (one at a time) includes searching for multiple targets. Everything within the spot can be processed in parallel; things outside the spot, or peripheral vision, are processed serially.

4.3 Control of Visual Attention

Control can be top-down (goal driven) or bottom-up (stimulus driven). [21, 22] Goal driven includes shifts of attention to spatial locations whereas stimulus driven is attentional capture by spatial cues, visual salience, and by abrupt visual onsets. The user employs strategies and intentions (i.e. looking for a target). When a person is searching for a featural target, then irrelevant targets will capture attention. However, when a person is searching for a more complex object, irrelevant featural targets will not capture attention. Stimulus driven attention is controlled by some salient attribute of the image that is not necessarily relevant to the user's perceptual goals (i.e. selecting a moving target because it "pops out".) When a person

Basic Features in Visual Search

Motion- Easy to find a moving stimulus among stationary distractors.

Color – Can be done through transformations

Size – How large the target is

Number - Set size – Miller's Magic Number

Resolution – How much acuity the user has

Time – Latency of data can confuse the user

- **Pictorial depth cues** 3D appearance of stimuli can make the search more efficient.
- **Stereoscopic depth** Efficient search is possible when the target item lies at one depth and the distractors lie at another.

directs attention to a spatial location in advance of a display, then visual events that would otherwise capture attention will

generally fail to do so. Stimulus driven control is both faster and more potent than goal driven attentional control due to the decision process that is required in goal-driven control.

Limitations of human attention which the automation designer must keep in mind include:

- Perceptual Processing Limitations Increased perceived difficulty attending to more things at one time.
- Focus of Attention Impact of the situation on the user in directing the attention and keeping it focused.
- Central Processing Limitations Cognitive processes may be limited in number which can occur at a time.
- Memory Long, Working, Short relationship between attention, working memory, search, short-term retention.
- Modes of Attention Top-down or Bottom-up

4.4 Guided Search to control attention

Factors to consider when designing presentation from Level 4 to Level 5 include redundancy of information already monitored during passive supervisory control. It may be critical to avoid cluttering the information display when switching from passive monitoring to active open-loop decision-making Level 5 activities, since time is usually of the essence in closing the loop on the Level 5 user decision and returning the system to automatic control.

Semantics and Syntax of Information presentation: The syntax, or form, of the information presented to Level 5 should accommodate known human factors issues to expedite decision making and lead to best-case true-successful decisions more often than false-failure decisions based upon incomplete or confusing information presentation. Semantics, or content and context, of the information is also important to presentation. False-failures can be defined as decision failures (with respect to desired outcome) not from human decision making failure, but from arriving at the correct decisions with respect to faulty information which leads to an undesired or failed outcome. In other words, false-failures would not be the fault of the HIL, but of faulty system design in how information necessary for the decision was presented to the HIL.

Visual search strategies are employed in HIL monitoring of any Group Tracking activity, which indicates key human factors such as visual memory load, visual processing workload, and visual search difficulty for a Group Tracking exercise. These factors also must be incorporated into the design and modeling of Level 5 User Refinement. For instance, visual search strategies are trainable in part, and may generalize across different tasks, different locations within the visual field, and across eyes [25]. It is also proposed that visual working memory usage does not negatively impact visual search, except perhaps a slight latency. [26] These factors in visual and other modalities must be researched and accounted for in particular implementations of presentation of fused sensor data for time-critical decision making. The LOA selected will depend on the nature of the interactions of the HIL attention factors with the automation. Finally, training of the HIL, or the novice status or expert status of the HIL, must be taken into consideration for both multi-modal attention parameters.

4.5 Trust in Automation

Several theories and working models of trust in automation for the HIL have been proposed and incorporated into both research and design. Information which is presented for Decision-Aiding to the HIL is not uniformly trusted and incorporated into SA. Rempel, in 1985, proposed three increasing levels, or 'stages of trust', modeled on human-human interactions: **Predictability, Dependability,** and **Faith**. Participants progress through these stages over time in a relationship. The same was anticipated in human-automation interactions, either via training or experience. The main idea is that as trust develops, the HIL will make decisions based upon the trust that the system will continue to behave in new situations as it has demonstrated in the past.

Trust issues in automation have been characterized and researched by Muir and Moyer. "The human operator's role in today's highly automated systems is to supervise the automation and to intervene to take manual control when necessary. An important determinant of operators' choice of manual or automatic control may be their degree of trust in the automation. The model of human trust was developed by taking models of trust between people as a starting point and extending them to the human machine relationship." [27]

Another construct of trust related to automation, outlined by Barber, 1983, and reviewed by Endsley, outlines the following:

- **Persistence** an expectation of constancy and predictability.
- Technical competence Expert knowledge, Technical facility, Routine performance
- **Fiduciary responsibility** Expectation that the automation will meet its design-based criteria for performance in domains where the machine has superior knowledge, authority, and/or power.

Sheridan [24] has written prolifically on automation and supervisory control. A review of this body of work is suggested to outline concepts of *reliability, robustness, familiarity, understandability, explication of intention, usefulness, and dependence* of automation to the user. Muir & Moray [12] built upon Rempel's stages and postulated that

Trust = Predictability + Dependability + Faith + Competence + Responsibility + Reliability

Muir and Moray [12] further defined the construct of **Distrust:** (1) Can be caused by operator feeling that the automation is undependable, unreliable, unreliable, etc. and (2) Set of dimensions related to automation failures, which may cause distrust in automated systems (Location of failure, Causes of failure or corruption, Time patterns of failure).

A tabular summary below, adapted below from Muir and Moyer [12], depicts the quadrant of trust and distrust behaviors with respect to good or poor quality of the automation. Basically, if the outcome of a wrong decision to trust the automation is worse than the outcome of a wrong decision to not trust the automation, then it is critical to present the user with enough training to know when to trust the automation.

 Table 1. Trust, Distrust, and Mistrust, adapted from Muir and Moray 1996 [12]

Operator's trust & allocation of function	Quality of th 'Good'	e automation 'Poor'
Trusts and uses the automation	Appropriate Trust (optimize system performance)	False Trust (risk automated disaster)
Distrusts and rejects the automation	False Distrust (lose benefits of automation, inc. workload)	Appropriate Distrust (optimize system performance)

As noted earlier regarding attention, modeling systems for SA to support successful decision making must take into account the mental processing of information. Trust [28-30] in the automation clearly impacts the mental processing model for decisions, and this impact changes over time and experience with the automation. Therefore, dynamic models must be devised to account for this aspect of the HIL. For the Human in the Loop to refine the assessment for final decision that is passed up from Level 4 in an open feedback loop, the user must have trust in the automation regarding the validity and reliability of the information presented.

Note that at the macro level, supervisory control takes the individual operator fields of view and combines them into a battlefield or strategic theater view. Taking over

from Level 4 to a Level 5 User Refinement means either assuming manual control of an individual remote sensor, tactician, or vehicle from the automated system. Situation awareness at both micro and macro levels will be necessary. Therefore the data and information processing algorithms must be able to be decoupled from the automated global or strategic synthesis from Level 0 through Level 4, such that individual system components can be isolated for the Level 5 User. Information fusion at the lower levels must be logged and state maintained of key variables to permit the necessary decoupling of fused information for precision decision override by the HIL at critical points in a supervisory scenario.

Adequate and precise training and design iterations to present the information successfully in both fused and decoupled paradigms will require extensive testing to achieve good situation awareness for the HIL.

5. USER REFINEMENT FOR GROUP TRACKING

Group tracking is the ability to prosecute a set of targets in the environment. Such issues as occlusions and relations among targets are key attributes which make the workload and attention for the user different than a single target tracking problem.

5.1 Group Definition

We define a group as a collection of targets that are spatially and temporally

similar, move together, and have the same allegiance. For the case of spatial similarity, we use the validation region of a

Group Tracking

User Trust Issues

Confidence – target ID correct Security – that impacts assessed Integrity – only show what know Dependability - timely Reliable - accurate Trust – ability to control Familiar – practice and training Consistent - Reliable

tracking system to define where the targets occupy similar space. The temporally similar targets are cases where the group of targets are near to each other in the same time instant. Targets that move together can be defined as a group by direction and speed. We use past information to determine the movement history. Finally, the allegiance of the targets relies on the identity of the targets within the group. In the case that similar groups join as a single unit force, the group detector assumes targets that are of the same allegiance and movement. Likewise, targets which are spatiotemporally dissimilar are split into separate groups.

To reduce the workload to the human, we use the fusion system to group targets using a belief measurement. The belief in the target ID is related to the group, allegiance, object-type, and location information. For the case that a sensor is cued to observe the object, it's identity is calculated through beliefs of the object type which is determined from an automatic target recognition (ATR) algorithm from the fusion of various sensors or the trust the human has in the display. To update the confidence in the Group ID, we include various definitions of groups as shown in Table 2.

The definitions for group tracking follow from the location, movement, target attributes, and the group allegiance. One difficulty arises if the members of different groups include targets of the same type and allegiance which merge, split, or cross. For a scenario in which similar target types can be members of multiple groups, we use human user refinement for feedback of kinematic information to determine which of the same target types belong to which groups. To accommodate crossing groups, we delay the merging decision until sufficient time has been acknowledged to determine which targets belong to which groups based on a movement history. In this case, human information helps determine group identity. Table 3 shows the benefits of group tracking.

5.2 Group Tracking with User Refinement

In our study of group tracking with a user, we first started with the raw tracks. By investigating the display, we incorporated 1) directing attention, 2) reducing the workload, and 3) improving trust. In Figure 11, the raw tracks are presented. At first it was difficult to discern tracks. To direct attention, we included road networks which also increased trust, as shown in Figure 12 Second, we use color and different lines that reduced the workload. Finally, we looked at displaying regions of interest to facilitate understanding the threat and directing attention to nearer targets (shown in Figure 13).



Figure 11. Raw tracks

Figure 12. Tracks with Road Networks.

Figure 13. Tracks with Regions of Interest.

Designing the tracking algorithms with the goal of Level 5 User Refinement requires determining the severity of trust outcome failures, and mitigating these. Therefore, the issues such as reliability of the system and validity of the information presented by the system are accounted for in modeling and design of Level 5 interactions regarding achieving appropriate trust of the HIL for the system. Finally, training of the HIL is an ongoing necessity to maximize the effect of the User Refinement upon the tracking model.

Table 2: Group Definitions:		
Attribute	Definition of measurement	
Spatial Temporal Kinematic Type Features Allegiance	 Location (i.e. clustering) Historical (i.e. tracking) Direction, speed, acceleration Vehicle (i.e. Tanks, trucks) Attributes (i.e. Wheeled, tracked) (i.e. friend, foe, neutral) 	

Table 3: Benef Attribute	fits / Attributes of Group Tracking Benefit
Speed Direction Spatial ID	 Splitting, termination of groups Crossing groups separation Merging , initiation of groups Allegiance determination Update occluded targets Improved track maintenance Increase group ID accuracy

6. CONCLUSIONS

This article overviewed some current fusion models and demonstrated the importance of the human in a fusion model. The higher-level fusion issues of control, decision, and action need to be addressed in current fusion system designs to effectively include the human in prosecuting target localization and identification. For the development of a human-machine inter-active fusion model, the use of the human in a Level 5 process was further assed using situation awareness, trust, attention, and workload measures. Results show that designing for User Refinement, with respect to HIL attention, workload and trust in the automation, can enhance the accuracy of the target localization and group identity.

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