Collaborative Human-Computer Decision Making in Network Centric Warfare

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Abstract

The shift from platform-centric to network-centric warfare (NCW) will introduce new layers of human decision making complexity never before experienced in command and control. The success of NCW will hinge on the ability of networks to provide information to support shared situation awareness between both humans as well as automated agents such as unmanned air, ground, and underwater vehicles. Of particular concern will be how to classify, filter, and synthesize enormous amounts of information generated by NCW sensors, all to generate a critical decision under time pressure and uncertainty. Automation can aid in that it can quickly sort, filter, and optimize a set of multi-objective cost functions, but a known limitation for intelligent automation is its inherent brittleness and lack of flexibility. This paper will discuss the development of visualization tools for multi-objective cost functions, as well as interactive sensitivity analysis tools. It is critical that visualization tools convey both quantitative and qualitative information to ensure constraints are not violated, and aid in determining how decisions affect both local and global mission goals, with the overall goal of providing a robust solution exploration space. With effective collaborative decision support, it is possible that when humans and computers collaborate, they can discover solutions superior to the ones determined independently of the other.

1 Introduction

Information sharing and collaboration between both humans and automated systems in order to enhance the quality of information and shared situational awareness is a fundamental tenet of Network Centric Warfare (NCW) (DoD, 2001). In NCW, operators will be expected to leverage multiple information sources for decisions under significant time-pressure and uncertainty. However, increases in available information sources, the volume of incoming information, and the operational tempo will place higher cognitive demands on operators, which could become constraints limiting the success of network centric processes. One potential strategy in dealing with the voluminous information that could saturate networked forces is to augment command and control decision processes with increasing levels of automation. Because of the large problem space in NCW both in terms of information sources and possible actions, automation is clearly warranted in attempting to filter and synthesize data to provide human decision-makers with recommended solutions. However, it is not clear that computer-generated solutions are always the best solutions.

Computer optimization algorithms like those needed to solve problems in large spaces with many variables and constraints can only take into account those quantifiable variables identified that were deemed to be critical in early design stages. For command and control scenarios, it is not possible to include every single variable or combinations of variables that could impact a final solution. In addition, it is not clear exactly what characterizes an “optimal” solution in command and control scenarios. While in manufacturing and in the financial domain, the notion of optimal can take on specific meaning, in the command and control arena, the need to generate an “optimal” solution should be weighed against a “satisficing” solution (Simon, 1955). Because constraints, variables, and rules of engagement are dynamic in combat environments, a definition of optimal is a constantly changing concept. Thus in the case of command and control decision making, especially in time-critical scenarios where loss of life could result, having a solution that is good enough, robust, and quickly reached is generally preferable to one that requires complex computation and extended periods of times, which may not be accurate due to incorrect assumptions.

Recognizing the need for automation to help navigate complex and large problem spaces like those in NCW, it is equally important to recognize the critical role that humans play in these decision making tasks. Optimization is a computational word typically associated with computers but humans are natural optimizers as well, but not necessarily in the same linear vein as computers. Because humans can reason inductively and generate conceptual representations based on both abstract and factual information, they also have the ability to optimize based on qualitative and quantitative information, something that is not within the computer's reach as of yet. In addition, allowing operators active participation in decision-making processes provides not only safety benefits, but promotes situation awareness and also allows a human operator, and thus a system, to respond more flexibly to uncertain and unexpected events (Parasuraman, 2000). Situation awareness has long been recognized as a critical human factor in military command and control systems. Military command and control centers must attempt to assimilate and reconstruct the battle picture based on information from a variety of sensor sources such as weapons, satellites, and voice communications.

Given that automation and humans each bring strengths and weaknesses to command and control decision making processes, instead of a mutual exclusive assignment of decision making functions to humans or computers, a possible better system architecture could be a mutually supportive environment in which the human and computer collaborate to arrive at a solution superior to the one either would have come to independently. In command and control domains in which mission goals are driven by human intentions and actions, and then executed and communicated through advanced automated technology, little research has specifically addressed how humans and automation can collaborate in planning and decision making. To this end, this paper will discuss development of visualization tools for multi-objective cost functions, as well as interactive sensitivity analysis tools that attempt to provide operators with a collaborative decision space. It is critical that visualization tools convey both quantitative and qualitative information to ensure constraints are not violated and to determine how decisions affect both local and global mission goals.

2 Levels of Automation

Human-in-the-loop designs which employ automation for redundant, manual, and monotonous tasks relieve operator workload in many cases, however, when the human is removed from active engagement in a decision process, unintended consequences can sometimes result. There can be measurable costs to human performance when automation is used, such as loss of situational awareness, complacency, automation bias, and skill degradation (Parasuraman, Sheridan, & Wickens, 2000). The "black box" approach to full automation can be useful for redundant tasks that require no knowledge-based judgments, but the subsequent lack of system understanding and loss of situational awareness that full automation can cause could lead to unanticipated effects for more complex tasks. However, function allocation between humans and computers does not necessarily have to be all or nothing, and there are varying degrees of automation which can be introduced in a decision support system.

Various levels of automation can be introduced into decision support systems, from fully automated where the operator is completely left out of the decision process to minimal levels of automation where the automation only makes recommendations and the operator has the final say. For rigid tasks that require no flexibility in decision making and with a low probability of system failure, higher levels of automation often provide the best solution (Endsley & Kaber, 1999). However, in systems like those that deal with decision-making in dynamic environments with many external and changing constraints, higher levels of automation are not advisable because of the risks and the complexity of both the system and the inability of the automated decision aid to be perfectly reliable (Wickens, 1999). Known as the "brittleness problem", automated decision-support algorithms are typically "hard-wired" in initial design phases, and thus are not able to account for and respond to unforeseen problems (Guerlain, 1995; Smith, McCoy, & C. Layton, 1997). Since by their very nature command and control events are unanticipated events and automation is inherently brittle, the human ability to detect, accurately assess, and respond must be supported.

The various levels of automation that can be incorporated into a decision support system are depicted in Table 1, and are known as the SV levels as they were originally proposed by Sheridan and Verplank (Sheridan & Verplank, 1978). Several studies have indicated that when a computer makes a recommendation (LOA 4), humans have a tendency to believe the automation, even in face of an erroneous solution, otherwise known as automation bias (see (Cummings, 2004) for a review). Tasks requiring higher cognitive processes of planning and learning, like those needed in command and control, require knowledge-based behaviors and a critical element of decision support system design is recognizing which knowledge states would be lost if higher levels of automation were used.

Table 1: Sheridan & Verplank Levels of Automation

Automation Level	Automation Description
1	The computer offers no assistance: human must take all decision and actions.
2	The computer offers a complete set of decision/action alternatives, or
3	narrows the selection down to a few, or
4	suggests one alternative, and
5	executes that suggestion if the human approves, or
6	allows the human a restricted time to veto before automatic execution, or
7	executes automatically, then necessarily informs humans, and
8	informs the human only if asked, or
9	informs the human only if it, the computer, decides to.
10	The computer decides everything and acts autonomously, ignoring the human.

The concept of automation levels have also been applied to a few military command and control projects. In an UAV Air Force sponsored effort, Ruff et al. (Ruff, Narayanan, & Draper, 2002) studied the impact of manual UAV control versus higher levels of control. They determined that an intermediate level of management-by-consent was preferable to manual or more fully automated control, termed management-by-exception. Limited automation level research was conducted for control of Tomahawk missiles, however, the research was constrained to examining possible bias issues between SV levels 3 and 4 (Cummings, 2004). This research demonstrated that subjects tended to be biased by automated recommendations. In another study concerning the development of a human-machine interface for control of UAVs from a single seat fighter cockpit (Howitt & Richards, 2003), variable levels of human and computer autonomy are under consideration, but as of yet, no experimental research results have been published.

For command and control missions that require human supervisory control, SV levels 2-6 are candidates for human-computer collaborative design, but as previously discussed, it is not always beneficial to incorporate higher levels of automation. To further explore how humans and computer can collaborate across the levels instead of exclusively relying on a single level, two case studies will be presented that illustrate how specifically mission planning tools can be used in a collaborative manner. The first is a resource allocation tool and the second is a path planning tool.

3 Collaborative Mission Planning Tools

3.1 Tomahawk Mission-Missile Matching

An example of a mission planning problem that could benefit from collaborative human-computer decision making is the mission-missile assignment problem for Tomahawk strike planners. Tomahawk missiles are long-range, subsonic cruise missiles used for land attack warfare and can be launched from up to more than 1000 miles away from their intended targets, with an accuracy of meters. The Tomahawk can carry one of three different types of warheads: penetrating, unitary and submunition. They are launched from U.S. Navy surface ships or submarines from pre-planned geographic locations known as “launch baskets”. While missions are planned weeks in advance, the actual missiles to be used are not known until hours before a strike because of the uncertainty of both launchers and ships’ arrivals in the launch basket. Because of this gap in mission planning and mission assignment, planners are confronted with a last minute resource allocation problem which is very labor intensive. Currently strike coordinators generate mission-missile assignments using a simple database called PC-MDS. The Personal Computer - Mission Distribution System is used to display and distribute the mission database, which contains all the mission data uploaded into missiles, such as terrain contour matching data, GPS (Global Positioning System) and/or DSMAC (Digital Scene Matching Area Correlation) data. PC-MDS does not provide any support for decision making and assignments are manually generated by strike coordinators, using either pencil and paper, or their memory to keep track of the different factors and options to consider (Cushing, 2003). This process is time and resource consuming because of the variety of parameters available.

In order to address this mission planning problem, an interface was developed (Figure 1) to allow a planner the ability to enter all relevant data for missiles, targets, and preplanned missions, and then match the missiles to the missions with the aid of some level of automated assistance. For each mission, the assignment task consists in finding the corresponding available resource (missile) that matches the mission requirements, such as warhead type, navigation equipment, and launch basket (and hence one or more ships that will be assigned to that launch basket). The main difficulty in the matching process is to take into account each piece of information that can potentially optimize the final assignment of missiles to missions.

Several types of information are available to the operator to make assignment decisions: hard constraints, probabilistic information, and optimization information. "Hard constraints" refer to those pieces of information that strictly determine a mission-missile match: for example, some missions can only be assigned to a penetrating missile, because the targets of those missions require a penetrating warhead. In addition, the operator may need to consider probabilistic information. In this model, we assigned to each missile a virtual firing rate corresponding to each ship's rate of success in missile launches (note that this is not a real world value but an artificial representation of probabilistic information). An operator may decide to prioritize those missiles coming from a ship with a high firing rate. However, the problem then becomes how to balance the assignments when using select missiles which reduces the number of possible total assignments. Finally, the operator can be asked to minimize or maximize some cost function. This optimization information would be used to achieve some "optimal" resource balance. For example, an operator may want to consider the number of days to port for the ships, in order to prioritize the use of missiles aboard ships that are due to port shortly (in order to minimize the number of weapons entering the port).

The complexity of the task results from the need to simultaneously consider and balance the three different information types which consist of hard constraints, probabilistic information, and optimization requirements. For example, between two missiles that both meet the hard constraints, is it better to choose the missile that has a firing rate of 80% (success of launch) and 30 days to port, or a missile that has a 65% firing rate but 5 days to port? Depending on the current constraints, one might be more appropriate in a certain type of environment than the other. Indeed, if the strike coordinator is told that the corresponding target must be destroyed at any cost, then the former missile with the highest firing rate may be chosen, whereas in another situation the strike coordinator may decide to reduce the total quantity of weapons for a particular ship because it is going back to port and general safety concerns have arisen.

Hence, generating a solution (a mission-missile assignment) becomes very difficult for the human operator when all

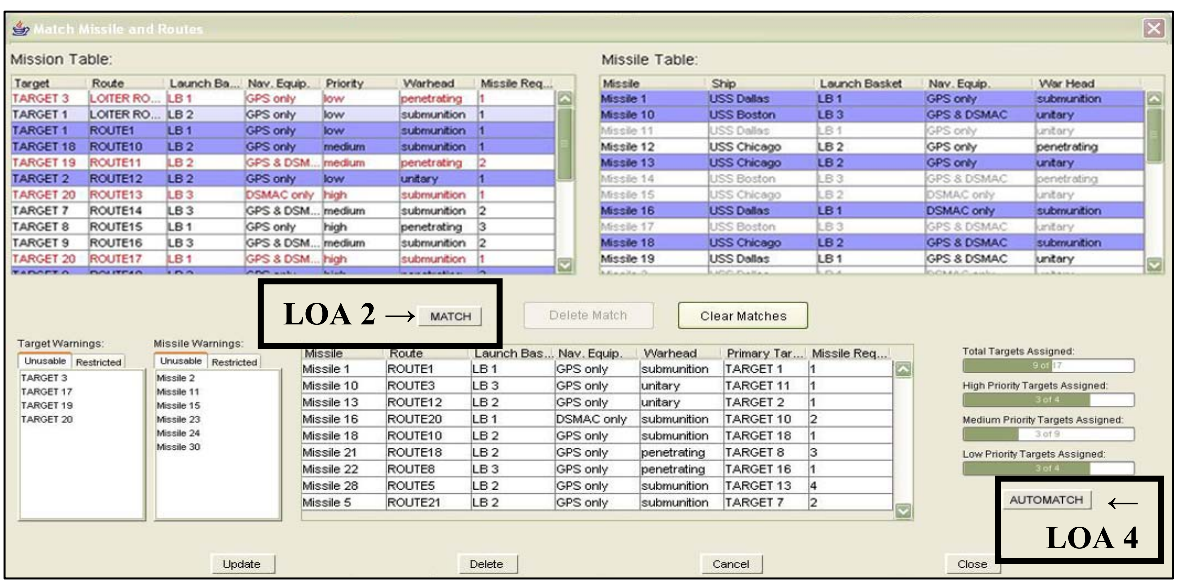

Figure 1: Mission-Matching Matching Interface 1

these parameters have to be simultaneously taken into consideration. The respective strengths of the human and the automation should therefore be balanced to create an effective and efficient assignment process that can generate a satisficing, or good enough, solution. The research question is to know what balance between humans and automation will be efficient.

3.1.1 The Matching Interfaces & Levels of Automation

3.1.1.1 Interface 1

The current matching interface (Figure 1) allows for manual matching (corresponding to LOA 2 where the computer only provides basic tools such as sorting or filtering). Interface 1 also provides an automatch capability (corresponding to LOA 4 where the computer makes all assignments and the human is left with the decision to approve or not the computed solution). In the former setting, the operator selects a mission in the mission table and a missile in the missile table (among those which have been filtered out by the computer as satisfying the hard constraints). The tables displays the primary characteristics of the missions (target, route, launch basket, navigation equipment required, priority, warhead required, and number of missiles required), and those of the missiles (ship, launch basket, navigation equipment available, warhead). Then the operator manually adds the match to the matching table. At the bottom left are warning tables that display the targets that cannot be reached (no missile can fulfill the hard constraints requirements), and the unused missiles. At the bottom right is a graphical summary of the current assignment, based on the matches included in the matching table. The horizontal bars fill in according to the number of targets assigned so far, with a breakdown by target priority.

LOA 4 is embedded in this interface by the "Automatch" button. When the operator clicks on Automatch, an algorithm instantly generates a mission-missile assignment and stores it in the matching table. Then, the operator has the option to manually modify this solution if deemed necessary. The heuristic search algorithm implemented in automatch sorts the missiles by priority. The missiles that have the fewest number of missions they can fulfill based on hard constraints are ranked first (this is to increase the number of assigned missions). Then, for each missile, the potential missions are prioritized in this order of importance: 1) loiter missions (the missile hovers over an area waiting for an emergent target to pop up), 2) high priority target, 3) medium priority target, and 4) low priority target.

3.1.1.2 Interface 2

Interface 1 does not allow for any real collaboration between the human and the computer, only basic filtering. Interface 2 (Figure 2) was created to leverage the computer's computational power, under human control. Interface 2 still includes the mission, missile, and matching tables, allowing for manual matching. The automatch button (LOA 4) is also available. But additional features have been included for LOA 3 purposes in which the computer narrows the selection to a few alternatives. For this level, we provide an interactive level where the human operator and algorithm work

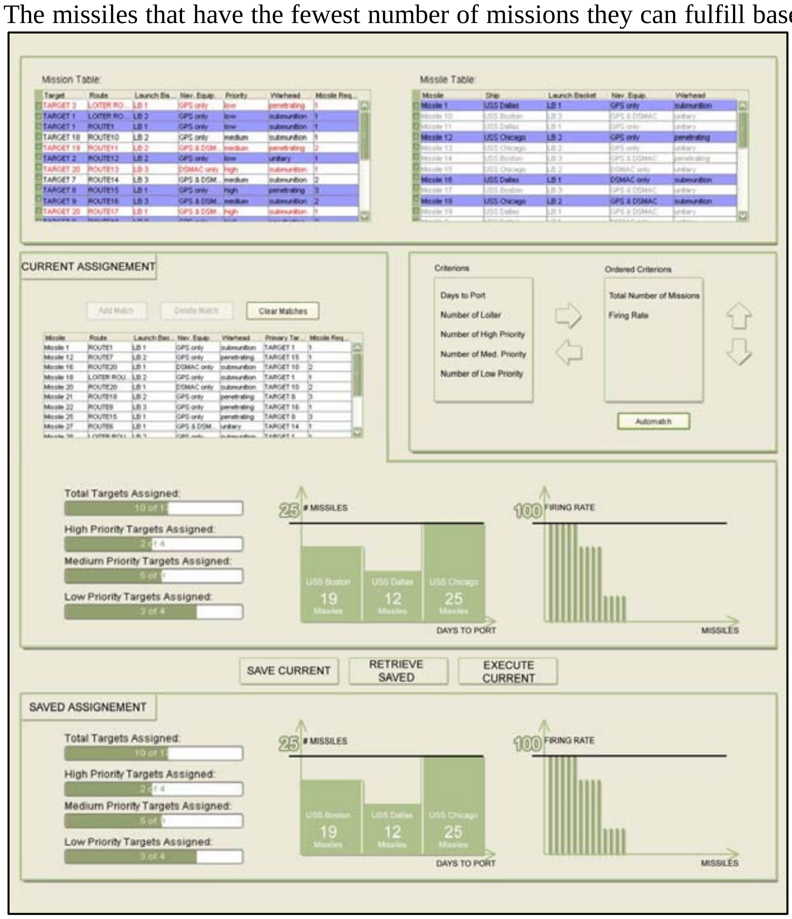

Figure 2: Matching Interface 2

together to solve the problem (called "collaborative matching").

First, the automatch is customizable. Whereas in Interface 1 the matching algorithm was completely hidden from the operator, in Interface 2 the operator can actually choose what criteria to include in the automatch, as well as a prioritization order between these criteria. Also, tick boxes next to the mission and missile tables enable the user to select a subset of missions and / or missiles to be considered by automatch.

Furthermore, the assignment summary has evolved to include, in addition to the horizontal bars, two other graphics that synthesize the assignment through the probabilistic (e.g. Firing Rate) and optimization (e.g. Days to Port) data. Finally, this interface includes a "save" option. When used, the current assignment is stored at the bottom of the screen, and a new assignment can be generated without modifying the saved assignment. This provides the user with a what-if comparison between two solutions.

3.1.1.3 Interface 3

Interfaces 1 and 2 are both based on the use of raw data while Interface 3 (Figure 3) is completely graphical. The automatch button at the top is similar to that in Interface 1. However, the user can act on the level of prioritization of the probabilistic information (Firing Rate) and optimization information (Days to Port), in the automated algorithm, *via* the central screen sliding bar (the "prioritization bar") that represents what criteria (Firing Rate or Days To Port) should take precedence on the other in automatch.

The result of the assignment computed by automatch is displayed in two ways. First, the breakdown by mission priority (loiter, high, medium, low) in the four corners shows numerically and visually (position of the cursor in the vertical column) how many missions have been assigned, with a secondary breakdown by warhead type. Then, the shaded area above and below the prioritization bar metaphorically represents the level of assignment: the more missions have been assigned, the more filled in the central area is. A complete assignment (all missions assigned) would be represented by a completely shaded central area. When the automatch solution is modified by the user, the new solution appears in green, and the first automatch appears as a pale gray in background, for comparison purposes.

Additionally, the user can require the computer to search the solution space to accommodate specific needs: by clicking on the up or down arrows of the cursors in the vertical sliders, the user instructs the computer to find a way

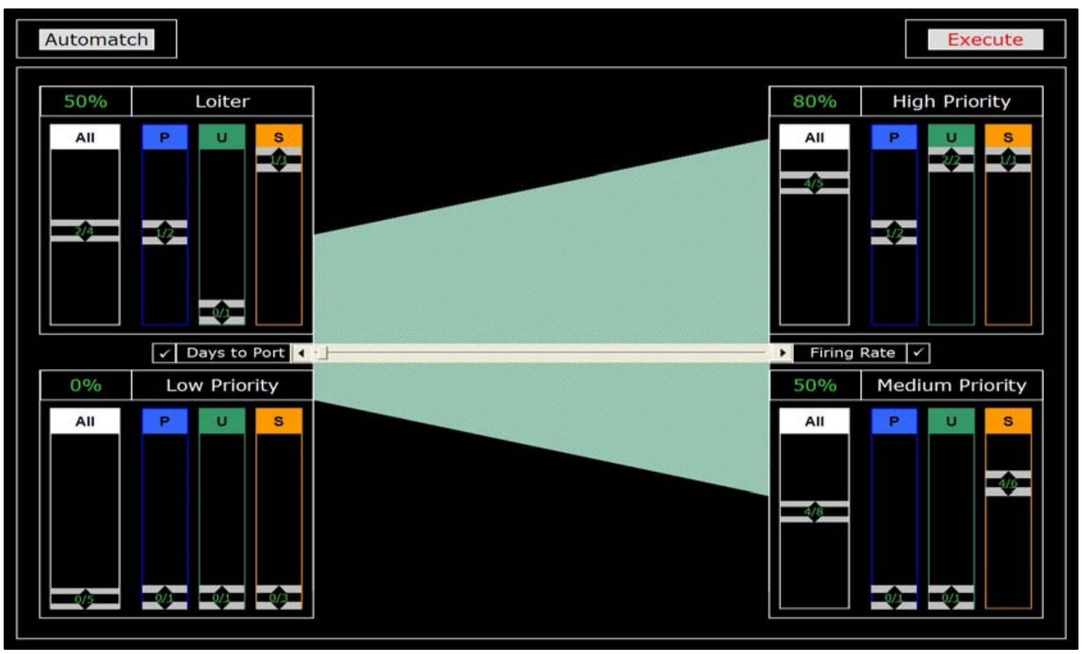

Figure 3: Matching Interface 3

to increase or decrease the number of assignments corresponding to the specific slider. Automatch will then compute a new solution to accommodate for this requirement, by potentially modifying other assignments at higher priority levels.

3.1.2 Interface Comparison

User evaluation and testing was conducted on a relevant military population with the three displays which generated critical feedback (Bruni & Cummings, 2005). While subjects agreed that the problem was too complex and cumbersome for manual matching as depicted in Figure 1, there was mixed feedback as to whether interface 2 or 3 would be more appropriate. A significant problem with Interface 3 is that operators have no knowledge of the rules behind the process (just as in Interface 1), nor is the influence of the prioritization bar completely transparent.
However, one subject found Interface 3 "very intuitive, with the right amount of information to present to the operator. Not too much information, just the right kind of information that is the information on which you can easily act". Another subject said that Interface 3 is "a relief from all the raw data of [Interfaces 1 and 2]… but you lose in information precision, for example, what targets are reached".

Simplifying the interface by making it graphical is an important step for high levels of problem-solving. However, operators should also be allowed to go deeper for more detailed knowledge of the environment if needed. This could be enabled by either an optional access to raw data (to allow manual matching), or a specific mapping between the general graphics to the detailed source of information, that is either the raw data in tables or a topological map. This finding highlights that configural displays, although useful for displaying higher order relationships and leverage the strength of human perception, do not always provide the depth of information needed for complex problem solving and should not be used as stand-alone decision tools. Testing is currently underway to determine whether or not Interface 2 or 3 produces superior performance in the missile-mission matching task.

3.2 Human vs. Automated Path Planning

An additional area of interest to NCW mission planning is the concept of path planning in which a start and goal state are known, but the optimal (or near-optimal) path between the two is not obvious due to a number of constraints, obstacles, and variables. Path planning applies to many segments of NCW to include foot soldiers attempting to navigate from point A to B as well as Tomahawk missiles and unmanned vehicles which must determine optimal paths over the ground and in the air, often in real-time with the need to avoid obstacles such as threats, both known and emergent. Particularly problematic for humans evaluating an automated path plan in real-time is not only how to determine whether or not the computer's solution is correct but also how to possibly manipulate the path in order to meet a new condition unknown to the automation, all under the stress of time-pressure.

As in the mission-missile planner, it is not clear at what levels of automation can the computer provide the most help to humans without either overloading the operator with too much information or hiding too much information such that the operator has no idea how a particular solution came to bear. To this end, an interface has been developed (Figure 4) to attempt to determine both what levels of automation are best for human evaluation of a computer-generated path plan as well as how the complexity of a particular cost function affects the human's ability to understand the solution. For example, if a path planner simply optimizes a path between points A and B on shortest distance and avoidance of obstacles, humans can typically perform on par with a computer. However, when a human has to consider not only the shortest distance as well as the energy expended (either from the human metabolic cost or the UAV fuel cost) and select the optimal path based on optimizing both functions, it is not clear when and how the automation should be leveraged and what information should be visualized to provide maximal decision support without cognitively overloading the operator.

In the path planning interface in Figure 4, users can elect to either manually plan a route or select autoplan which causes the computer to generate an optimal solution for a cost function based on shortest distance, fastest time, and least amount of energy expended (metabolic cost). As for the missile-mission planner, the users have the ability to collaborate with the computer and select different aspects of the cost function to plan. Users can select all three of the variables individually or in a group to see both their paths over the ground as well as a trend analysis (lower section of Figure 4) to visualize where the greatest changes occurred. Testing is underway to determine what levels

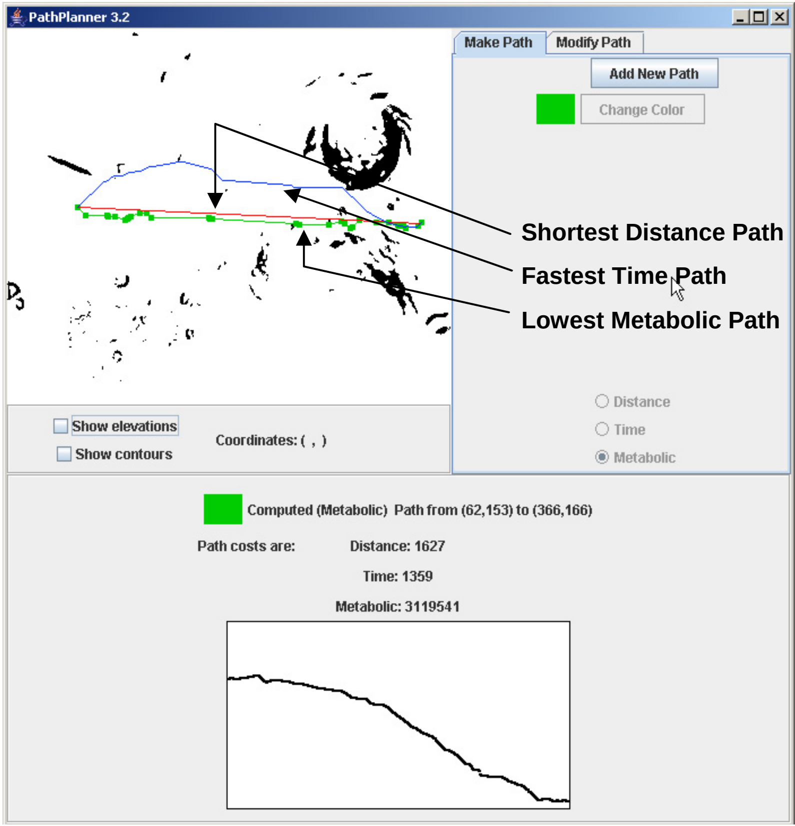

Figure 4: Collaborative Path Planner

of automation are most appropriate as well as how many variables a human can manipulate and arrive at an acceptable solution under time pressure.

4 Conclusion

In command and control domains in which mission goals are driven by human intentions and actions, and then executed and communicated through advanced automated technology, little research has specifically addressed how humans and automation can collaborate in planning and decision making. Automation can make computations quickly and accurately based on a predetermined set of rules and conditions, which is especially effective for planning and making decisions in large problem spaces like those in command and control domains. However, computer optimization algorithms are notoriously "brittle" in that they can only take into account those quantifiable variables identified in the design stages that were deemed to be critical. In contrast, humans can reason inductively and generate conceptual representations based on both abstract and factual information, thus integrating qualitative and quantitative information. However, humans are not able to integrate information as quickly as a computer and are susceptible to flawed decision making often based on a set of heuristics, which are inherently error-prone.

The shift from platform-centric to network-centric warfare will introduce new layers of human decision making complexity never before experienced in command and control. The success of NCW will hinge on the ability of networks to provide information to support shared situation awareness between both humans as well as automated agents such as unmanned air, ground, and underwater vehicles. While automated decision support tools are critical in aiding decision makers by filtering, synthesizing, and prioritizing incoming information, it is also equally necessary to allow humans the ability to collaborate with automation so that the human can intervene in contingency and unexpected scenarios. The development of visualization tools for multi-objective cost functions as well as interactive sensitivity analysis tools can provide operators with leverage points into the automation but to be effective, it is critical that visualization tools convey both local and global mission goals as well as associated constraints. It is possible that when humans and computers collaborate, they can discover solutions superior to the ones determined independently of the other.

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