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Paper Session I-A - Use of Neural Networks as a Range Safety Decision Support System

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Use of Neural Networks as a Range Safety Decision Support System

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ABSTRACT

Current range safety processing and display systems are generally limited to presenting the Range Safety Officer with a display of flight vehicle position, impact, and performance data in conjunction with off-nominal performance destruct criteria. The decision to take any flight termination action, based on the presented data, is primarily left to the Range Safety Officer. While still maintaining the man-in-the-loop concept, neural network based artificial intelligence systems could be employed as Decision Support Systems (DSS) to assist the decision making process of the Range Safety Officer. The adaptive nature of a neural network allows it to "learn" from the data it is presented with and, over time, become an increasingly intelligent DSS. This paper describes ENSCO, Incorporated's investigation of where and how neural networks could be employed as real-time DSS tools in the range safety decision making process. This paper will detail an ENSCO, Inc. investigation of how a neural network approach can be a viable asset to the range safety decision making process. The use of neural networks as tools to increase public safety is a feasible methodology that should be further investigated as a potential way ahead for future range safety technology programs at spaceports and launch ranges.

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Abstract

Whenever a rocket, including the Space Shuttle, is launched as part of the U.S. Space Program, safety features are in place to ensure that human life, health, and property are protected. Since the protection of personnel and property safety relies on accurate knowledge of where flight vehicle debris would land in the event of a mishap, range safety critical systems must precisely process and display data from the rocket and ground sensors (e.g., Radar, Optic Tracking Sites). It is imperative that these range safety personnel and critical systems properly process the data to produce an accurate vehicle's Instantaneous Impact Position (IIP).

Current range safety processing and display systems are generally limited to presenting the Range Safety Officer (RSO) with a display of flight vehicle position, impact, and performance data in conjunction with off-nominal performance destruct criteria. The decision to take any flight termination action, based on the presented data, is primarily left to the RSO. While still keeping the man-in-the-loop concept, neural network based artificial intelligence systems could be employed as a Decision Support System (DSS) to assist the decision making process of the Range Safety Officer. The adaptive nature of a neural network allows it to "learn" from the data it is presented with and, over time, become an increasingly intelligent DSS. This paper describes ENSCO's investigation of where and how neural networks could be employed as real-time DSS tools in the range safety decision-making process. An investigation was conducted using a simplified neural network. The results proved that the current technology for neural networks is not at the stage where it could be part of the decision making process. However, certain aspects of a DSS can be used as a RSO tool to increase public safety and is the way ahead for the future of range safety technology.

Introduction

Assuring the proper operation of range processing systems is critical to launch operations and the protection of life and property in the launch area. For this purpose a broad suite of tracking instrumentation monitors manned and unmanned vehicles launched at the U.S. Eastern Range (ER). The primary requirements for all tracking and processing systems are set forth in the Eastern-Western Range Requirement 127-1, Range Safety Requirements (EWR 127-1, 1999). A prime EWR 127-1 requirement for the protection of life and property is the real-time knowledge of where a flight vehicle is and where flight vehicle debris would impact in the event of an anomaly. To accommodate the requirement for debris impact determination, range safety display systems encompass a process known as IIP processing and display. The IIP process works in conjunction with the present position data by constantly taking the present position data, assuming thrust is terminated, and applying a ballistic trajectory calculation algorithm to the position data, thus determining the ground impact location of the vehicle. This IIP is plotted on the range safety display screens along with the present position of the vehicle. Destruct criteria are based on the predicted location of falling debris, rather than the actual position of the missile.

Range instrumentation used to maintain positive knowledge of the flight vehicle's position includes telemetry reception and processing sites, ground-based radars and optical trackers. Launch vehicles all include a flight telemetry package to report comprehensive vehicle performance parameters including Inertial Guidance (IG) data that is received at a series of telemetry sites throughout the ER.

The Problem

During any particular mission, the launch vehicle's data is processed through a real-time system for input to a set of range safety displays used to monitor the vehicle during ascent. The most critical users of this information are Range Safety Officers who perform the critical task of protecting public safety by monitoring the instantaneous vehicle impact position throughout the flight, and terminating the mission when that safety is threatened. A range safety system processes positional data from the vehicle, optical trackers, and radars and graphically presents the vehicle's location. Unfortunately, the RSO is overloaded (Figure 1) with information and must react to information within seconds whether or not to destroy a multi-million dollar mission. His split-second decision will be scrutinized for months following a mission. The RSO needs a tool to analyze the situation and make a decision recommendation on whether or not to terminate the mission.

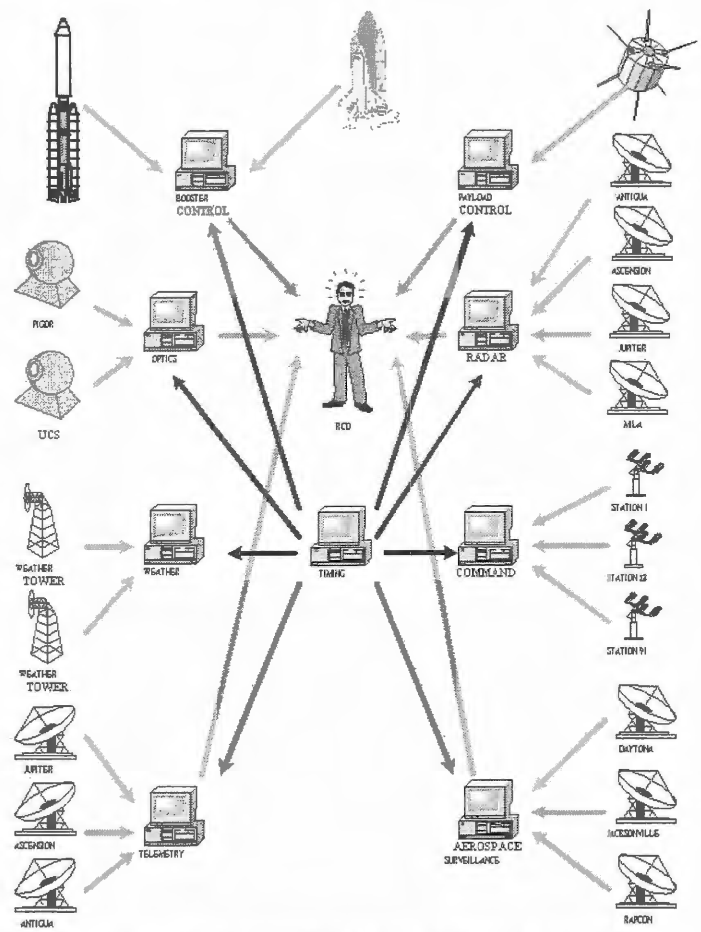

Figure 1. Real-time Decision Making Overload

Methodology

Decision Criteria

People are good at judgment, understanding, reasoning, problem solving, and creativity. Computers are good at remembering lots of facts, searching through large quantities of data quickly, and multi-tasking. One of the application programs for a computer is a Decision Support System (DSS). The goal of a DSS is to assist a manager in making an intelligent decision (Turban, 2001). The goal of an expert system is to design a general-purpose search algorithm that was capable of stringing together elementary reasoning steps to find a complete solution (Stuart Russell, 2003).

Our DSS will have a large number of inputs. Each rule will be checked to see if its premise is satisfied and if true, fire the rule. This rule interpretation, as it is called, is a process of matching, conflict resolution, and execution (Figure 2).

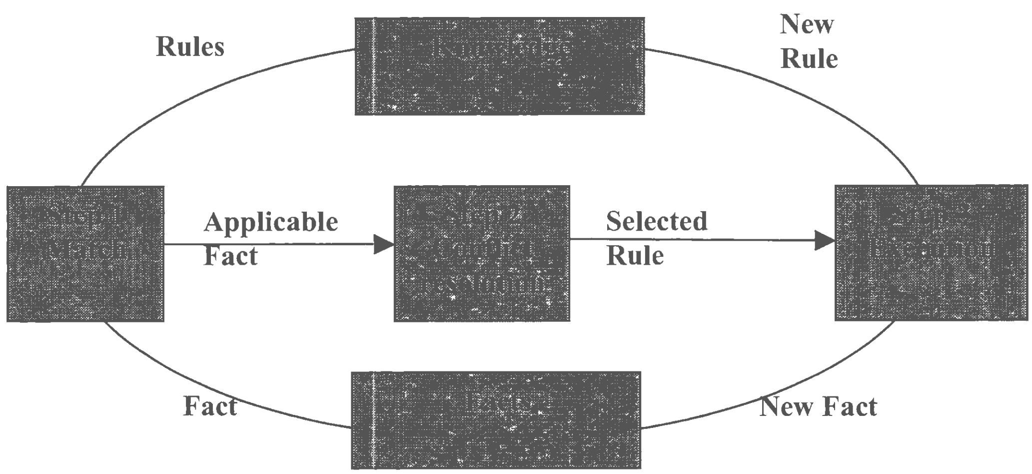

Figure 2. Forward Reasoning Inference Process

Matching determines if the rules premise is satisfied, conflict resolution determines which rule will fire if multiple rules are satisfied, and execution of the rule which will assert or retract facts and/or new rules. Since the system has a small number of inputs compared to outputs, a forward chaining goal-driven method will be used. There are two basic architectures: inference networks and pattern-matching systems. An inference network is more simplistic to implement; however, they are less powerful since all combination of relationships have to be known up front. Inference networks can be easily represented as a node graph where we can visualize the knowledge base as a network. However, there are other cases where it is impossible to visualize the relationship of the networks, which is where pattern-matching systems are best suited. Pattern-matching systems process facts to derive new facts and search the fact database for matching patterns.

Where Neural Networks Fit in the System

This study concentrated on various aspects of how a Neural Network could provide an adequate flight termination decision-making tool for launch operations. A Neural Network closeness to the structure of the brain makes it a candidate for research in the decision making process. The brain is made up of interconnected neurons while a neural network is made up of interconnected processing elements called units that respond in parallel to a set of input signals given to each. The unit mentioned above is equivalent to its counterpart in the brain, the neuron. (Ingrid Russell, 1996). The more abstract properties of neural networks has interested researchers in AI for years, especially their ability to perform distributed computation, to tolerate noisy inputs, and to learn. We now have a better understanding of other systems such as Bayesian networks; however, neural networks remain one of the most popular and effective forms of a learning system and are worthy of further research (Stuart Russell, 2003). ENSCO researched whether a neural network could be used to predict a trajectory path during periods when the RSO is blind. The Range Safety System calculates and displays the number of seconds based on the current velocity to the closest destruct line (Figure 3).

Figure 3. RSO Display with Destruct Lines (red)

The study used existing trajectories to train a neural network. The next step was to simulate data outages and compare the predicted output to the measured output. While the neural network roughly predicted the measured output, the large fluctuations made it impractical for actual use (Figure 4). Even small fluctuations in a vehicle's Earth-Centered Earth-Fixed (ECEF) Geocentric Orthogonal Cartesian Coordinate system will have a huge impact on a vehicle's IIP. Unfortunately, this eliminates using a neural network as a viable tool.

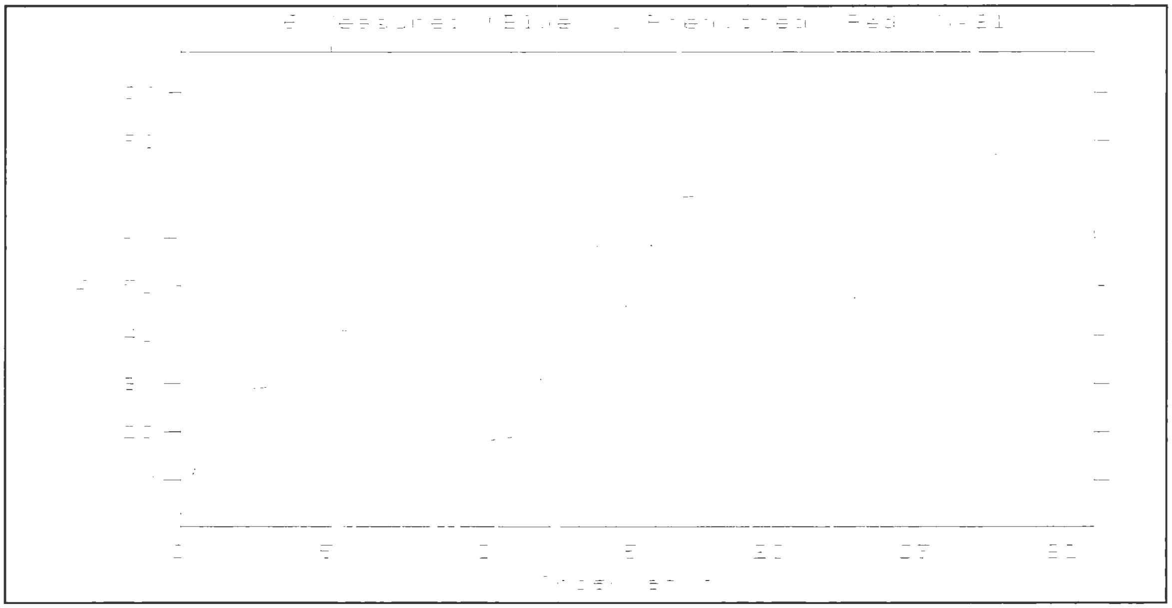

Figure 4. Neural Network Trajectory Model

Conclusion

It takes several hundred men and women to successfully launch manned and unmanned vehicles from Cape Canaveral Air Force Station (CCAFS) and Kennedy Space Center (KSC) in Florida. The RSO is a critical member of this team and has the huge responsibility of making split-second decisions concerning public safety. Unfortunately, the research conducted on using neural networks did not meet the desired results; however, certain aspects of intelligent decision-making tools have a place in the range safety process and should be researched in the near future. A specifically tailored DSS would greatly enhance the RSO capability to perform his/her duties while increasing public safety.

Future Research

While this study has eliminated a neural network as a viable tool based on the current technology that is not to say it should not be researched further in the future. In addition, this research has raised other questions. For example, range safety versus mission assurance. Just because a vehicle successfully passes through the African Gate does not necessarily mean that it still is not a threat to public safety. Other recommendations could also be made to the RSO, for example, even though a vehicle is projected to impact a populated area, should it be destroyed. In other words, would there be less loss of life by allowing one large object impact versus many smaller objects. A computer could quickly model and make recommendations based on the vehicle's velocity, mass, and the population density. This decision may change as altitude increases the probability of small debris burning up upon re-entry. Future research could even include a prototype for an Enhanced Range Safety System (ERSS), which would run in parallel with the current system and make real-time decision recommendations based to RSO based monitor booster position, velocity, acceleration, and health. We see a system like ERSS as the "Way Ahead" for the future of Range Safety.

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