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Application of Expert Systems to Military Leadership Training

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Abstract: In the US Military, leadership decision making is trained using various scenario-based simulations. Unfortunately, in these simulations the missions are preplanned with deterministic actions and counteractions. This allows the military student to learn and ultimately anticipate predictable simulation actions resulting in inefficient training. This research uses expert systems to enable more realistic scenarios for the training event by adding stochastic effects. Two key variables that are never guaranteed at the time of mission execution are the availability of systems equipment and the environmental conditions, in this case weather. One of the key stressors to add into a leadership training event is the reduction of the use of various tools as well as the visibility of the trainee such as Electro-Optical sensors which are particularly vulnerable to environmental hazards. By introducing such hazards into the training simulation, the training becomes more realistic by limiting the availability of certain tools the decision maker can use (i.e. IR sensors, night vision devices, visual aids, etc.) and reduction of human visibility so the desired learning outcomes are improved. This paper provides an example of the use of a neuro-fuzzy system to simulate these environmental hazards.

Keywords: Military Training, Neuro-Fuzzy, Fuzzy, Naturalistic Decision Making

1. Introduction

Military leadership development provides continuing training to strengthen an officer's decision-making skills. However, most traditional training, such as military mission planning, is a static desktop effort that develops Courses of Action (COA) and simulates operations against a "red team" with predictable tactics (i.e. no uncertainty is involved in the resultant output). These Red Teams usually consist of fellow officers, sailors, and civilians who have been trained in traditional adversarial tactics to act as the opposing forces (OPFOR) for given mission scenarios. In computer simulations, the Red Team missions are preplanned, without consideration of current real-world empirical data and with no randomness in their actions or counter-actions. This allows the military student, over time, to learn and ultimately "game" the system by anticipating predictable red team actions resulting in inefficient training because of the deterministic scenarios. Such a simulation gives rise to the potential use of expert systems and computational intelligence to add dynamic variable uncertainty into the scenarios. The two key variables that are never guaranteed at the time of mission execution are the availability of sensor systems and the actual environmental conditions during the mission, in this case weather. This paper describes the application of a neuro-fuzzy system to simulate the uncertainty of the "fog of war" in the training model. This is accomplished by degrading the capabilities of various sensor systems and adjusting the model user's visibility by modifying the electromagnetic spectrum using a shallow neural network to classify various environmental hazard outputs and then applying a fuzzy inference system to the degrees of severity of the meteorological environmental states. This application of a neuro-fuzzy system is one example that shows the capabilities of expert systems to improve the military student's decision making in a training scenario.

2. Related Research

Significant studies have been completed on behalf of the U.S. Army and Navy researching decision making since the 1980s (Li et al., 2020; Perrin et al., 2001). As the military acknowledged naturalistic decision making (NDM) in its leaders, their focus has been on risk analysis and mitigation as part of their mission pre-planning activities. Multiple qualitative and quantitative studies have developed risk and resilience assessment models that have been incorporated into mission planning (Curt and Tacnet, 2018; Rehak et al, 2019; Richards, 2020). Some studies have applied artificial intelligence methods to risk analysis and naturalistic decision making (Ibanez and McCalley, 2011; Lam and Tai, 2018; Muller, 2012). Several fuzzy inference systems were presented in a few papers to address uncertainties in risk assessment yielding an output more precise and reliable than traditional expert inputs alone (Markowski & Mannan, 2008, Skorupski, 2016, Kuklev et al., 2018). A key component of improving the military commander's decision-making capabilities using AI is to also incorporate machine learning. As machine learning continues to mature, various techniques are being developed which address unique significant events or situations, known as "one-shot learning". These types of events are very common in military operations and such techniques are very applicable for potential use in this research. However, the current literature is notably deficient in the research of the application of computational intelligence to improve decision making or other aspects of mission planning. This is especially true in the military domain, including training, where senior leaders have acknowledged that such data analytics and processes are woefully behind the current state of technology. The use of artificial intelligence is still a "future research" commentary (Li et al., 2020) will little to no thought of its applicability to prescriptive mission planning training to improve military decision making.

3. Methodology

3.1 Background

As part of the mission planning training simulation, the trainees have access to various sensor systems as well as defensive and offensive weapons systems. Such systems utilize various target identification technologies and methods such as radar, infrared, laser, as well as visual and are known as Electro-Optical (EO) systems. Each of the systems in the model operate along the electromagnetic (EM) spectrum in the EO spectrum as shown in Figure 1 below (Navy, 2005). These systems are dependent upon the visual or infrared contrast to find and identify objects. The contrast is influenced by various environmental factors, including temperature. In the physical world these systems are degraded to varying degrees due to environmental conditions. Such degradation is known as EM extinction which is a function of absorptivity (a) and scattering (s). The Navy's professional development pamphlet of *Atmospheric Effects on EO Sensors and Systems* written by the Naval Meteorology and Oceanography Professional Development Detachment Atlantic (June 2005) describes absorption and scattering. Table 1 below shows the wavelength range of various environmental particulate sizes (Navy, 2005). This data will serve as our neural network output variables as well as fuzzy membership for the fuzzy model.

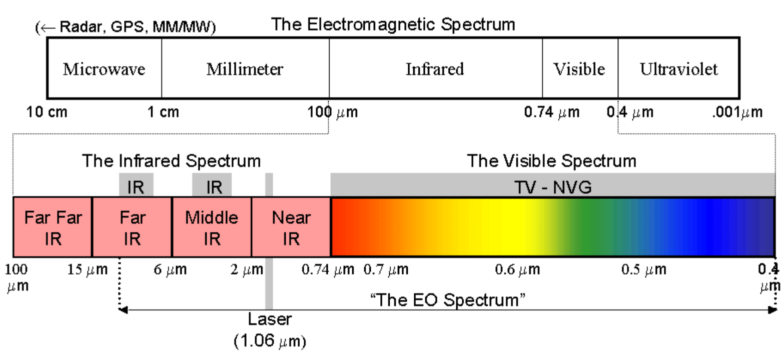

Figure 1. VIS / NVG / FLIR EM spectrum

Table 1. Average particulate sizes

Particulate	Average Size
Haze	0.05 to 0.5 microns
Smokes	0.2 to 2 microns
Dust	1 to 10 microns
Fog, Clouds	0.5 to 80 microns
Fumes	up to 100 microns
Mist	50 – 100 microns
Drizzle	100 – 500 microns
Rain	500 – 5000 microns

3.2 Data Preprocessing

The dataset used was from Kaggle database that provides environmental sensor data which can be found at Environmental Sensor Telemetry Data | Kaggle to train this neural network to pick the predominant environmental hazard to be used in the simulation. This initial dataset provided 405,184 observations of real-world environmental conditions from three sensor arrays. Since the base dataset does not provide correlating input variables or desired output variables, significant data preprocessing was required to obtain the desired data outputs and establish the synthetic database to be used in this project.

Initially, several input variables were removed as they provided no information relative to the desired output. Furthermore, the categorical variable of motion was converted to a binary identifier for the presence of wind. The dataset provided six input variables of Carbon Monoxide, Humidity, Wind, Pollutants, Smoke, and Temperature. The nine desired outputs of Haze, Smoke, Dust, Fog, Fumes, Mist, Drizzle, Rain and Wind needed to be developed and incorporated into the dataset. The output variables are calculated as binary variables where 1 indicates the presence of the given output and 0 indicates the given output is not present. The presence of the Wind is a direct correlation to the Wind input which has already been converted to a binary observation. Haze, Smoke, Dust and Fumes are determined by establishing a minimum threshold of the associated input variables utilizing first principles and general assumptions to indicate the presence of the output variables. The presence of Fog as an environmental hazard occurs when the variance between air temperature and dew point is less than 2.5 degrees Celsius (4.5 degrees Fahrenheit) (Fog 2022). For this model, we assume the Humidity variable observed in the initial dataset is equal to Relative Humidity. For Mist, Drizzle, Rain, generalized assumptions were used to translate the real-world observations based upon the value of the Humidity input variable. The resultant output provides a priori information from which the neural network can be trained. Because of the variance in distribution of the outputs, the data was normalized as part of the preprocessing effort.

3.3 The Neuro-Fuzzy System

Combining a neural network with a Fuzzy Inference System (FIS) in sequence, the neuro-fuzzy system first utilizes the optimized neural network to identify the environmental hazard to be applied to a given military training scenario based upon various inputs into the network model by the training scenario moderator. Once the hazard is identified, the EO FIS will provide suggested degradation of various sensor systems and the Visibility FIS will provide the visual range available to the training students based upon the same initial inputs from the scenario moderator.

The intent of the neural network portion of model is to identify the various environmental hazards based upon given inputs. Using the MATLAB Neural Network Toolbox, a model was developed to train, test, and validate the classification of the environmental hazard outputs. The model design consists of a two-layer feedforward network with ten sigmoid hidden neurons and nine linear output neurons. The model was trained using the Levenberg-Marquardt algorithm. The output of this neural network is the identification of which of the eight environmental hazards used in this model are present for a given scenario based upon inputs provided by the user.

Once the hazard is identified using the trained network, the model then conducts fuzzification of the membership sets for the environmental hazard and visibility. It is assumed that absorption is out of scope as its calculation has dependent variables that are not measurable. Fuzzy set theory establishes the nonstatistical uncertainty as low, medium, or high based upon the particulate size ranges provided in Table 1 resulting the membership set as depicted in Table 2.

Table 2. Environmental Hazard Wavelength Severity

Condition	Wavelength Severity (in microns) Low	Medium	High
Haze	0.05	0.225	0.5
Smoke	0.2	1.1	2
Dust	1	5.5	10
Fog, Clouds	0.5	40.25	80
Fumes	0	50	100
Mist	50	75	100
Drizzle	100	300	500
Rain	500	2750	5000

Assuming the model's initial starting point for each evaluation is a clear day with no electromagnetic extinction, nor infrared emissivity, the environmental state of the simulation will begin with the crisp electromagnetic spectrum value, EM, is 0.4 at the top of the visibility spectrum. The desired output is the new electromagnetic spectrum value, EM*, based upon the electromagnetic extinction, k, as determined by the Type I Mamdani Fuzzy Inference System of the various environmental conditions and their associated values which will shift the resultant EM* to the left of the electromagnetic spectrum as measured in microns. The centroid defuzzification algorithm utilizes the simple equation as follows:

$EM^{*}=EM+k$ where (1)

$k = \sum_{n=1}^{8}(a + s_n)$ where a = absorption and s = scattering (2)

The new crisp EM* value establishes the availability, accuracy, and degradation of various sensors and systems in the model as described in section I above. The membership functions utilize triangular probability with rule sets as follows:

1. If input X(n) is low then output Y(n) is low.
2. If input X(n) is medium then output Y(n) is medium.
3. If input X(n) is high, then output Y(n) is high.

Wind has a direct impact on the severity of a given environmental hazard. As such, the model incorporates an additional set of rules when wind is present with unique fuzzy impacts based upon low, medium, or high winds as shown in table 3 below. Like the random determination of the various environmental hazards, wind is stated as a binary variable where 1 indicates the presence of wind and 0 indicates no wind.

Table 3. Wind Fuzzy Rules

Condition	WIND Low	Medium	High
Haze	0	-1	-2
Smoke	0	-1	-2
Dust	+1	+1	+2
Fog, Clouds	+1	0	-2
Fumes	0	-1	-2
Mist	+1	+1	-1
Drizzle	+1	+1	-1
Rain	0	+1	+2

For Haze, Smoke, and Fumes, low wind has minimal impact, medium wind reduces the overall output by one level (high to medium or medium to low), and high reduces the overall output by two levels (high to low, medium to low). This is

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evidenced by real world weather measurements that indicate Haze, Smoke, and Fumes have their maximum impact in a static, no wind environment and the more wind, the less those hazards are present. Likewise, for Dust, Mist, and Drizzle the presence of low and medium wind actually increases their impact by one level (low to medium, medium to high) but high winds reduces Mist and Drizzle by one level while high winds increase Dust by two levels to the highest impact. Fog is a unique hazard in that low winds increase the presence of Fog (0-10 knots) while medium and high winds above 10 knots will remove it. Finally, for Rain, the impact to the output is minimal at lower wind speeds. However, the higher the wind, the more impact driving rain has on the overall extinction factor. As such, medium wind will increase Rain output by one level and high wind will increase Rain by two levels. Fully incorporating Wind into the model requires 72 additional rules to be applied. The resultant output establishes the extinction coefficient, k, which is then used to determine the new spectrum value, EM*, as described above. From this value, the simulation model will reduce the availability of the given electro-optical devices that are available to the trainee throughout the scenario.

A second component of this application of the "fog of war" to this model is the incorporation of the visibility of the user. Visibility is defined as the maximum horizontal distance through the atmosphere that objects can be seen by the unaided eye (Bennett, 2012). In order to maximize uncertainty in the training model, a second Type I Mamdani Fuzzy Inference System is developed to account for visibility. The Air Quality Index is a common measure used by governments to provide information to the public of how clean the air is on a given day and its resultant impact on human health. US National Weather Service data provides the degradation of human visibility based upon the air quality index established by the amount of particulates in the atmosphere and can be found at Visibility Guide to Smoke and Air Quality Now Available | NC DEQ. The air quality index data provided serves as the membership set to establish a second fuzzy algorithm focused on visibility to use in our training our model. Incorporating this into our model yields the visual range varying from 0–10 miles.

4. Discussion of Results

The results of the application of this Fuzzy Inference System provided a surface map of potential outputs for given inputs. Figure 2 below shows the output surface map for the scenario where wind and rain are present.

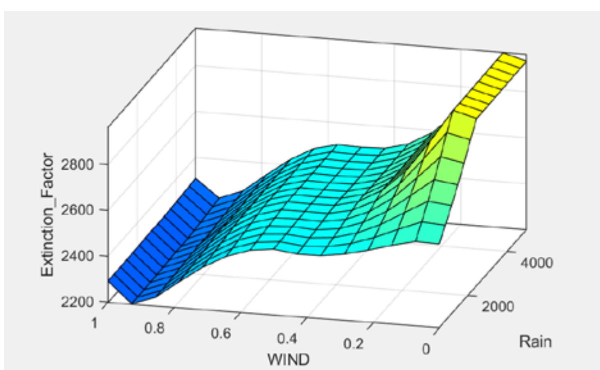

Figure 2. Output Surface map for Wind and Rain Inputs

Upon defuzzification, the model produces an environmental condition as well as the associated electromagnetic spectrum extinction factor crisp value. These two conditions are then incorporated into the Unity based training model to modify the scenario of the decision-making exercise both visibly as well as technically as the various electro-optical systems are turned off. For example, the output identifies Smoke as the environmental condition with a new EO spectrum value of 1.5µm. This value shows in Figure 1 the visible spectrum is degraded and only the infrared and laser systems will be available for this scenario. Like the results of the earlier Fuzzy Inference System, the resultant surface map of potential outputs for various inputs is shown in Figure 3 below which yields a visible range percentage to be incorporated into the training model.

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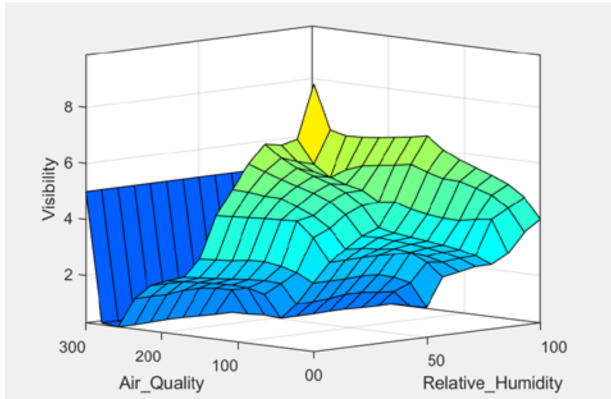

Figure 3. Visibility Output Surface Map for Air Quality and Relative Humidity Inputs

5. Conclusion

This paper demonstrates the use of expert systems in military training through the application of a neural network and fuzzy inference system to simulate the "fog of war." This was done by using computational intelligence to degrade the capabilities of various sensor systems and modify the electromagnetic spectrum associated with various meteorological environmental states with varying degrees of severity. In addition, uncertainty of the human visibile range was added to the model based upon the fuzzification of the amount of haze in the model's atmosphere as one example of the capabilities of expert systems to improve military training. The use of neural networks as approximations of the real world are adequate for improving military training through the use of stochastic simulation. The use of the MATLAB Neural Network Classification Toolbox provides the tool to efficiently develop the model to translate real world inputs into desired environmental hazard outputs. Additionally, using the synthetic dataset developed for this model, it was found that the Levenberg-Marquardt algorithm provides superior results in terms of mean squared error rates. The model developed for this application has been shown to properly classify the various environmental hazard outputs which are then incorporated in a training simulation to add uncertainty to various scenarios designed to improve the military student's decision making. The use of a fuzzy inference system to indicate environmental conditions properly mimics the real world in that such conditions are always a key factor in military decision making. Additionally, while meteorology provides quantitative forecasting, it is more fuzzy in reality and directly impacts the availability of various military systems as well as the visibility of the military user on every mission being conducted. The proper application of the fuzzy inference system produces more realistic environmental conditions that the military trainee can use to strengthen their naturalistic decision making.

6. Future Work

To further improve this system, a more focused investigation of the data as well as the use of other computational intelligence techniques would be necessary. To accomplish this, such investigation would require the observed hazard output to a given sensor data input to be included in the empirical data of the dataset in order to reduce the assumptions made in this current model. Additionally, various additional deep learning techniques should be applied to strengthen and validate the results obtained through the shallow learning methodologies utilized in this study. Also, applying fuzzy logic to other variables of the model as well as adjusting the assumptions could improve the impact to adding variability, thus improving the training experience. Specifically, to this model, utilizing a Type II fuzzy inference system would yield different results given the additional uncertainty due to the Type II system as well as the two input model.

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