Application of Multiple Artificial Intelligence Techniques for an Aircraft Carrier Landing Decision Support Tool

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Abstract - This paper describes some aspects of a recently completed project that improves the Landing Signal Officer's (LSO) decision making when guiding the landing of aircraft on aircraft carriers. The decision support aids were developed using multiple Artificial Intelligence (AI) techniques. The project developed pilot trending and flight prediction techniques as well as optimized the LSO's user interface via the application of decision-centered design methodologies from cognitive psychology. SHAI determined the significant aircraft approach parameters and developed a neuro-fuzzy system for plane trajectory prediction. SHAI also developed pilot trending techniques and software using case-based reasoning and fuzzy logic. In addition, in conjunction with many LSOs, we determined the best display options and most appropriate display logic for the information produced by the pilot trending module, and designed and implemented the resulting LSO interface. This paper concentrates on two particular areas of AI application, that is, the data fusion portion of the pilot trending system, and plane trajectory prediction.

I. PROBLEM STATEMENT

The aircraft carrier landing environment is an extremely complex one. In addition to operating what may be termed as an extremely busy airport, aircraft carrier landing operations are affected by a number of variables not associated with a normal airport. Of these, the most critical are fleet tactical considerations, flight deck space constraints, aircraft carrier maneuvering space (sea room), flight deck motion (pitch and roll), continuous mechanical preparations, resetting arresting gear and optical landing system between each landing, airborne aircraft fuel status, aircraft ordinance, minimal use of navigation, communications and RADAR emissions as in EMCON operations; and, above all, time constraints. The Landing Signal Officer (LSO) is responsible for each aircraft's final approach and landing.

During the last 60 seconds, the cognitive demands, namely the critical decisions and judgments, increase quickly until a decision to wave off (i.e., abort landing), or not, is made. The LSO, and not the pilot makes the wave-off decision. Often times the ship is heaving 10 ft. up and 10 ft. down, making a 20 ft. displacement from a level deck. In addition, it is often difficult to see the aircraft approach during night operations, and impossible to see during stormy conditions at night. The LSOs must rely on auditory cues and the equipment at the *LSO station* to assist their decision-making. For the project described in this paper, we were tasked with designing a decision support tool to enhance the LSO station, in order to assist LSO decision-making and hopefully increase the amount of time to make a correct wave-off decision, which is usually from 0.5 to 4 seconds before landing. The photographs in Figure 1 show LSOs on the deck of an aircraft carrier guiding in an aircraft, and an LSO monitoring an aircraft momentarily before touchdown.

Figure 1. Landing Signal Officers at Work

This paper concentrates on two challenges of the project, whose solution utilized AI.

- Data fusion of a linguistic data source and a numeric data source (see Figure 2), and
- Aircraft trajectory prediction.

One of the challenges encountered was that inferences needed to be drawn based on correlations between a data source in linguistic form and a numeric data source.

Another major challenge was aircraft motion prediction. Essentially the problem is that of time series prediction in which past and present motion profiles are presented to the prediction system and it is required to predict the motion in the next few seconds. The system can be trained with past data before it is engaged in the on-line prediction task.

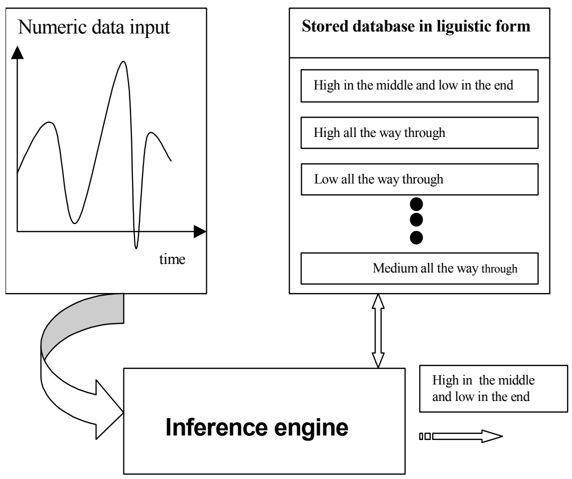

Figure 2. Numeric/Linguistic Data Fusion

II. SOLUTION OVERVIEW

A fuzzy logic based approach is used to infer the correlation of landing data in linguistic and numeric formats, where both data sources are characterized by noisy and incomplete data. By correlating the numerical motion trajectories with the previous grading of related aircraft approaches in a linguistic database, similar approach information is presented to facilitate decision-making.

A neural network based fuzzy inference system [1] approach for time-series prediction was determined to be the most successful approach for solving the aircraft motion prediction challenge. Many techniques were considered and tested including statistical [2], adaptive signal processing [3], and other transform and machine learning [4] techniques. A database of landing trajectories of different pilots flying various aircraft was used to train the system for subsequent prediction purposes. The goal was a projection 2 seconds ahead of the current flight position.

III. FUZZY LOGIC IN THE DATA FUSION OF LINGUISTIC & NUMERIC DATABASES

Existing Navy databases store trajectory descriptions in two formats: landing signal officers' linguistic comments describing the previously executed landing approaches and numerical RADAR data, which provides information about the current landing trajectory. Numeric RADAR data is not stored for all landings, so only the linguistic comments are available for the majority of past landings.

Each landing approach is subdivided into 5 stages based on the aircraft's distance from the ship's deck; these stages describe how far away the landing aircraft is from the deck. LSOs' comments are recorded in a special shorthand code, which describes various aspects of the pilot's approach for each landing stage. The following sample comments illustrate the use of LSO's shorthand code:

H(LUL)X	High and a little lined up left at the start.
HFIM	High and fast in the middle
NEPLOIC	Not nearly enough power, very low in close

The stage comments are combined to create a linguistic description of the entire landing trajectory:

(HX) NEP.CDIM LOBIC-AR A little high at the start. Not enough power on come down at the middle. Low and flat from in close to at the ramp.

A. Numeric Motion Profile

When a plane is attempting to land on a the aircraft carrier, the landing signal officer's comment describing the pilot's performance is not yet available to the decision-support system described herein. However, the ship's RADAR constantly monitors the pilot's progress and relays the numerical aircraft position data to the decision-support system. This motion profile provides the basis for analysis of the current landing trajectory and allows for its comparison with previously executed landings.

B. Data Fusion using Fuzzy Logic

Fuzzy logic is employed to perform numeric-to-linguistic conversion in order to ensure a homogeneous data format necessary for information fusion. The landing trajectory is represented as deviations from perfect lineup (i.e., side-to-side) and perfect glideslope (i.e., height). Fuzzy lineup and glideslope functions were determined from analysis of Navy data are shown in Figure 3. The lineup category consists of 7 fuzzy sets, ranging from significant left lineup (_LUL_) to significant right lineup (_LUR_). The glideslope category is subdivided into 7 analogous fuzzy sets, which construct a "very high" (_H_) to "very low" (_LO_) classification of the aircraft's glideslope. These fuzzy sets map directly onto the comments used by LSOs to describe the aircraft's position.

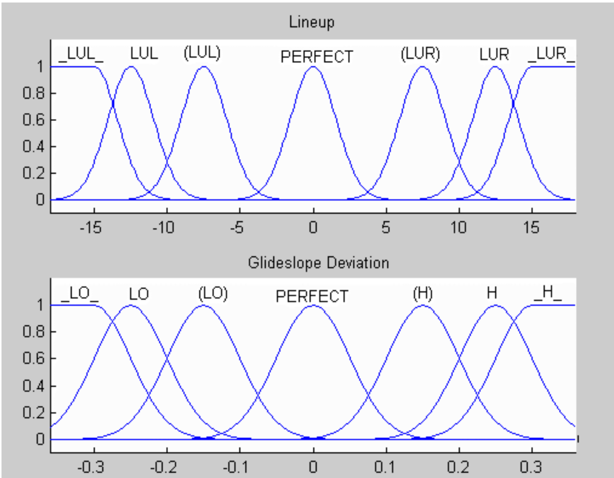

Figure 3. Lineup & Glideslope Fuzzy Membership Functions

Similar fuzzy definitions are constructed for various other parameters that define the landing trajectory. These fuzzy concepts enable the system to classify any point in the landing trajectory by associating fuzzy membership values with it.

The system used case-based reasoning [5] to retrieve previously stored linguistic cases most closely resembling the current landing trajectory by computing a *similarity measure* of the current numeric trajectory with respect to each stored linguistic comment. The data fusion using fuzzy logic is used as part of the similarity measure calculation. Similarity measure is computed online every time the approaching aircraft passes the next landing stage. Each time a similarity measure is recomputed, exponential forgetting is used to assign higher weight to the most recent stage of the landing.

IV. PLANE TRAJECTORY PREDICTION

To guide an aircraft to land more safely and smoothly aboard aircraft carriers, LSOs need the ability to predict how the aircraft motion trajectory will continue. This ability is mainly learned via experience and the fact that all LSOs are themselves pilots. However, SHAI was tasked with attempting to develop a system to predict the plane position 2 seconds hence. This task consisted of solving a time series prediction problem in which past and present motion profiles are provided to the prediction system in order to predict the motion in the next few seconds. No other information was provided to base the prediction on, such as present engine setting or wind speed and direction.

Typically, the flight pattern is carefully observed and guided when the aircraft is within one nautical mile (1 NM) of the landing deck in open sea. This corresponds to approximately one minute in real flight time. A RADAR system records numeric aircraft trajectory information. This data was used to train a system for subsequent prediction purposes. Thus the general problem was to take as input, time-series profiles with a maximum duration of about 1 minute and provide a 2 second hence prediction of the plane's location. This problem is depicted in Figure 4.

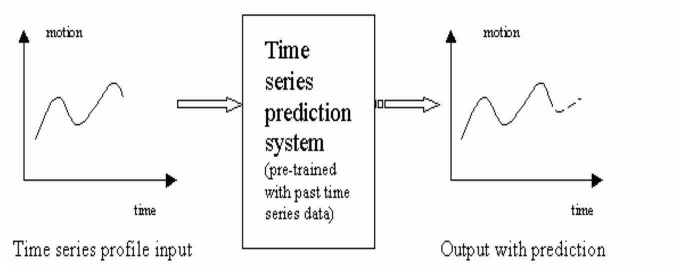

Figure 4. Time Series Prediction

The data provided contains substantial noise, and the magnitude of the noise varied amongst the individual passes. Since the data includes noise and its nature was unknown, the difficulty of the problem was significantly increased. See Figure 5 for an example of noisy landing data. Many potential solution techniques besides the neural network based fuzzy inference system were investigated and none proved superior, although some provided similar levels of performance.

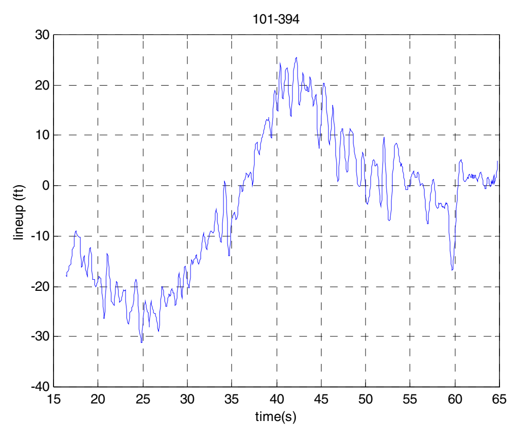

Figure 5. Position Data with Significant Noise

C. Neural Network Based Fuzzy Inference System

A neural network based fuzzy inference system [6] is a multi-layer network in which each node performs a particular function (e.g., a fuzzy function) on incoming signals (as well as a set of parameters pertaining to the node). The nature of the node function may vary from node to node, and the choice of each node function depends on the overall input-output function, which the neural network is required to carry out. A neural network has two types of nodes: an adaptive node (represented by a square in Figure 6) has parameters that may be updated by a learning algorithm, while a fixed node (represented by a circle) has none. A neural network

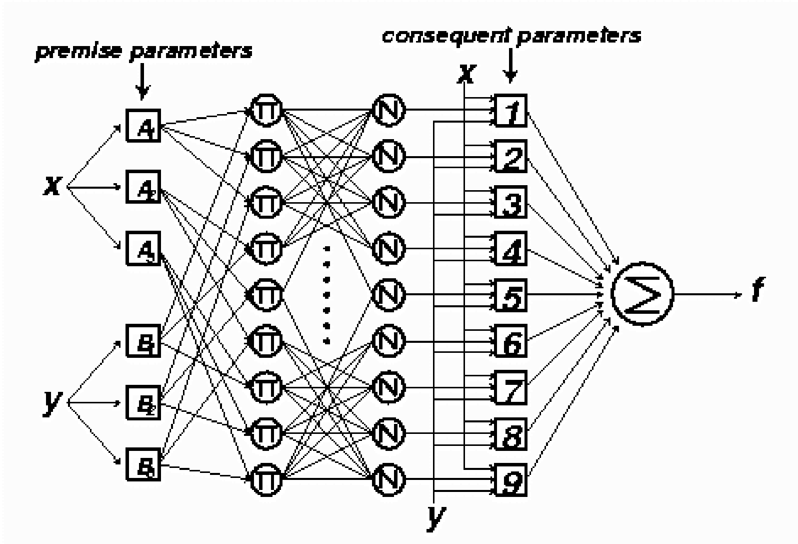

Figure 6. Neural Network based Fuzzy Inference System

based fuzzy inference system is comprised of several layers of nodes, as illustrated in

The node function of each node in the *premise* layer of nodes is a fuzzy membership function, which specifies the degree to which the node's input parameter satisfies some linguistic quantifier associated with the node. The Π layer of nodes outputs the firing strength of the fuzzy rules, and the *N* layer normalizes the firing strengths. The *consequent* layer performs (Sugeno-type) defuzzification, aggregated by a single weighed sum node in the *final* layer. The learning rule is a hybrid of gradient descent and least square estimation of parameters. In the forward pass of the learning algorithm, signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by gradient descent.

The system was trained with a subset of the past (noisy) RADAR data before it was engaged in the on-line prediction task. After training the system with a subset of the past profiles, the system was exposed to unforeseen approaches and forecast its profile in the next few seconds on-line.

Figure 7 shows a sample aircraft lineup trajectory (filtered position), the trajectory predicted by the neural network based fuzzy inference system (ANFIS), and the trajectory predicted by a 1st order polynomial extrapolation based upon the most recent several seconds of the trajectory (poly 1). The y value of each of the two prediction curves at time *t* shows the position that was predicted 2 seconds into the future at time *t-2*. As is typical with time series prediction algorithms, there is a tradeoff between algorithms that respond quickly to changes in recent data values and algorithms that are tolerant of noise.

A number of polynomial prediction algorithms based on various weightings were investigated with time windows for the 0th, 1st, and 2nd derivatives of the most recent *n* seconds of the trajectory. For each prediction algorithm, graphical analysis of the predicted trajectories was used to understand the types of prediction errors characteristic of each algorithm (undershoot, overshoot, and lag). In addition, the total prediction error across the duration of each trajectory was calculated. It was determined that the polynomial prediction that exhibited the lowest error was a weighted average of the current position and a linear (1st order) extrapolation of the last several seconds of the trajectory. That is, predicting the trajectory using 2nd order or higher polynomial terms tended to degrade the prediction. The neural network based fuzzy inference system outperformed this best polynomial prediction algorithm; see Figure 7.

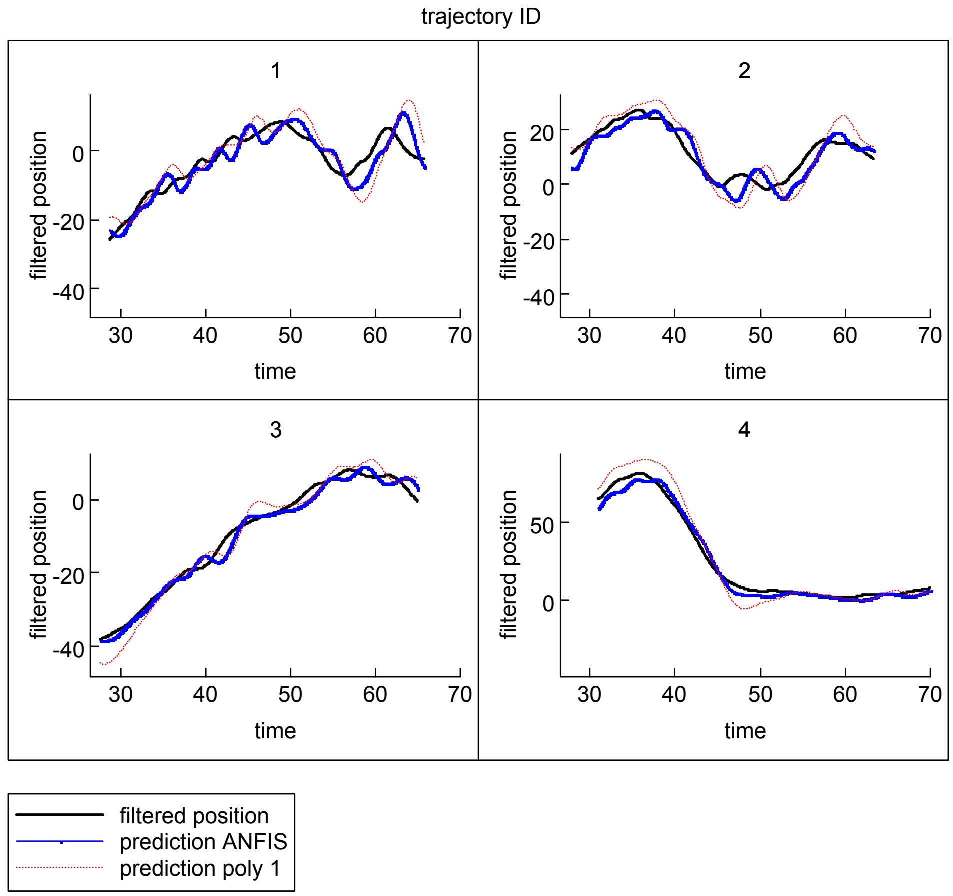

Figure 7. Comparison of neural network prediction

V. CONCLUSION

Artificial intelligence played a significant role in the development of SHAI's decision-support tool that will allow landing signal officers to make better time-critical decisions in a dangerous environment, where errors in judgment can and have lead to loss of life. Specifically a fuzzy logic approach was used in a case-based design for pilot trending, this paper outlined how fuzzy logic was used to solve the sub-problem involving data fusion of heterogeneous data. The paper also outlined the development of a neuro-fuzzy system for plane trajectory prediction, this technique proved successful at handling the significant noise in the data and provided predictions superior too many other techniques.

VI. REFERENCES

[1] Pao, Yoh-Han, Adaptive Pattern Recognition and Neural Networks, Addison-Wesley, 1989

[2] Pao, Neil A., Introductory Statistics 5th Edition, Addison Wesley, 1999

[3] Widrow, Bernard, and Samuel D. Stearns, Adaptive Signal Processing; Prentice Hall, 1985

[4] Mitchell, Thomas M., Machine Learning, McGraw-Hill, 1997

[5] Kolodner, Janet, Case-Based Reasoning, Morgan Kaufman, 1993

[6] Jang, Jyh-Shing Roger , Chuen-Tsai Sun, and Eiji Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Prentice Hall, 1996