W. E. Kelly and J. H. Painter, "Soft Computing in the General Aviation Cockpit"
Proceedings of the First On-line Workshop of Soft Computing, August 19-30, 1996, On the Internet, served by Nagoya University, Japan, pp. 151-156.

# Soft Computing in the General Aviation Cockpit

**Wallace E. Kelly, III**
Dept. of Electrical Engineering
Texas A&M University
College Station, Texas 77843
wkelly@ee.tamu.edu

**John H. Painter**
Dept. of Electrical Engineering
Texas A&M University
College Station, Texas 77843
painter@ee.tamu.edu

Abstract

*The aviation industry stands to benefit from the technological advances that have come to be known as soft computing. This paper describes how soft computing techniques are being used to improve a pilot's situational awareness. Of particular interest is the ability of a computer to add value to the raw sensor data, autonomously monitoring the aircraft's situation for possible anomalies in flight management. This function is performed by the Flight Mode Interpreter (FMI). The FMI is a fuzzy inference module which classifies the current aircraft state into operational modes. Examples are included of the FMI in operation. Concluding remarks summarize this written presentation and suggest additional areas that need to be addressed.*

## Introduction

The aviation industry stands to benefit from the technological advances that have come to be known as *soft computing*. In particular, the capability for increasing a pilot's situational awareness during a flight can improve safety and reduce the time required to train and maintain safe operating skills. Current techniques in soft computing can provide real-time procedural advice and critiques of present performance.

The authors of this paper are involved in an on-going avionics research project that has the goal of embedding a real-time, knowledge-based advisory and training system into the cockpit of general aviation aircraft. Termed *ASTRA* ©, the Aeronautical Safety and Training Rules Advisor is a real-world application of soft computing.

At the heart of this development of a pilot advisory system is the idea of an aircraft *metacontroller* proposed by Painter [1] and demonstrated by Glass [2]. A metacontroller differs from a flight control system in that a metacontroller generates high-level messages for the automatic flight control system auto pilot. The metacontroller relies on a computer-encoded knowledge base to give high level commands for flying the aircraft. The knowledge is encoded using fuzzy logic and expert system rules. The original Pilot Advisor and metacontroller concept were presented in [1]. The idea of a metacontroller gives a convenient hierarchical structure to the task at

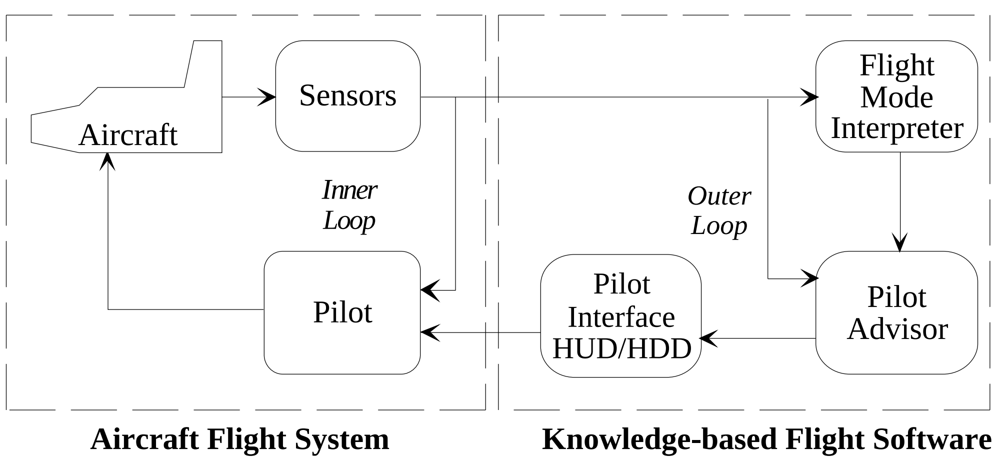


**Figure 1. Pilot advisory system functional architecture.**

hand.

The current state of the research does not pursue direct control of the aircraft, but rather seeks to aid the pilot through monitoring and advising. Figure 1 is a modification of the original system architecture that reflects this change in functionality. The domain of the encoded knowledge may be safety-related, navigational in nature, or simply related to aircraft performance issues. Such a pilot advisory system is a valuable step toward increased automation in the cockpit.

## System Architecture

There are four primary components to the current system architecture. The pilot and the aircraft are of course the central members of the overall system. The *Pilot Advisor* (PA) and the *Flight Mode Interpreter* (FMI) are the other two primary components. The PA serves the function of metacontroller. The PA and FMI are basically two software modules running in an on-board avionics computer. The Flight Mode Interpreter is a fuzzy logic system that classifies the current state of the aircraft into one of eight operational modes. The Pilot Advisor is an expert system that generates messages for the pilot based on the inferred flight mode, aircraft sensor readings, and information from the pilot. A special suite of sensors is necessary to interface the aircraft to the PC. A *heads-down display* (HDD) and a *heads-up display* (HUD) provide an interface to the pilot.

The Pilot Advisor is an expert system, with expertise in aircraft limitations, navigation, flight procedures, etc. It relies on the Flight Mode Interpreter to indicate the current operational mode of the aircraft. Based on that mode, the Pilot Advisor “fires” a set a rules that check physical limitations of the aircraft, displays information relevant to the current mode on the HUD and the HDD, and assists the pilot in flight planning. The PA manages displays on the HUD and HDD to provide the clearest possible view of the situation and to support pilot activities. A goal of the Pilot Advisor is to decrease the pilot’s workload during the flight.

## Flight Mode Analysis

The Flight Mode Interpreter is responsible for making a decision about the aircraft operating mode based on sensor information, navigational information, and mission planning. The FMI decreases the need for pilot input to the advisory system by automatically inferring the current stage of a flight. The advice, alarms, and symbology of the HUD and HDD are driven by the flight mode inferred by the Flight Mode Interpreter. There are four basic requirements of the FMI.

- It must provide the correct flight mode. The measure of the FMI’s performance is based on how closely the FMI can match a pilot’s *intended* mode.
- It must provide information about the certainty and confidence associated with the decision.
- It must be robust. That is, it must be able to make the mode decision even if not all the sensor readings point to the same mode.
- It must not be “nervous”. Quick oscillations between modes will translate into HUD symbology that blinks off and on, advice that is changing and perhaps even conflicting, and alarm messages that come and go.

The FMI classifies the current operating condition of the aircraft into one of seven “modes”. The seven operational modes are shown in Table 1. The classification is made based on eight input variables that are provided by the sensor suite of the aircraft. Table 2 lists the sensed values. These eight variables form an eight-dimensional space of aircraft operation.

| Operational Flight Modes |
|---|
| TAXI |
| TAKEOFF |
| CLIMBOUT |
| CRUISE |
| INITIAL APPROACH |
| FINAL APPROACH |
| LANDING |

**Table 1. Operational flight modes for the ASTRA project**

| FMI Inputs |
|---|
| Engine Power |
| Angle of Attack |
| Roll |
| Gear Setting |
| Flap Setting |
| Indicated Airspeed |
| Altitude |
| Rate of Climb |

**Table 2. Input variables for the Flight Mode Interpreter.**

At any given time in a flight, the aircraft’s state can be quantified as a single point in that eight-dimensional space. The job of the FMI is to partition that space into seven different operational modes.

## Fuzzy Inference

The concept of a *fuzzy set* was introduced by Lotfi Zadeh in 1965 [3]. The stated purpose was to deal with "classes" that have no "sharply defined criteria of class membership." Fuzzy sets allow the construction of system models when the sets that comprise the system are not clearly defined. Such is the case for the operating modes listed in Table 1. For the ASTRA project, fuzzy sets provide a way to partition the operating space into fuzzy, sometimes ambiguous modes.

A fuzzy set is completely defined by its *fuzzy membership function*, $\mu(x)$, which gives the degree of membership of an element, x, in a set. If $\mu_A(x) = 1$, x has “full membership” in the fuzzy set A. If $\mu_A(x) = 0$, x has “no membership” in the fuzzy set A. For $0 < \mu_A(x) < 1$, uncertainty or ambiguity exists which causes x be a member of A to some extent [4]. For our flight mode interpretation problem, the fuzzy sets are the flight modes (e.g., TAKEOFF, CLIMBOUT, CRUISE, etc.) and x is a vector of the current sensor readings.

The design of the FMI has been based on fuzzy logic. Fuzzy logic provides a good way to model the uncertainty associated with the flight modes. The uncertainty results from variation in pilot style and the inherent overlap of the modes in the state space.

It is interesting to note that the output of the FMI must be a crisp classification. Unlike a fuzzy control system which benefits from smooth transitions between control sets, the flight mode interpretation problem requires a crisp, discrete decision. Symbology on the HUD is either displayed or it is not displayed; alarms are either issued or not. There is no fuzziness in the end result. What then is the reason for using fuzziness in the classification process?

There are three motivations for using fuzzy logic in the Flight Mode Interpreter.

- While the flight mode decision is crisp, the rules for determining the mode are not. Fuzzy logic provides a framework for encoding that uncertainty into the FMI rules.

- Fuzzy rules also allow for resolution of conflicting data. If the rate of climb does not match the mode CRUISE, but all the other inputs suggest CRUISE, a fuzzy approach could still make a CRUISE decision.

- Finally, while the mode decision is crisp, the transitions between modes are not. Calculating a confidence and certainty about the fuzzy decision not only facilitates filtering the mode decision, but also gives the pilot an indication of the reliability of the Pilot Advisor’s messages.

There is a group of fuzzy logicians and statisticians who view fuzzy logic as a form of the Bayesian probabilistic approach to uncertainty and decision making. From a Bayesian point of view, the concept of a fuzzy set is analogous to a *subjective probability* [5]. Painter [6] has shown that, in fact, a common implementation of fuzzy logic can be formulated in Bayes notation. Due to the rich and proven heritage of Bayesian probability, the Bayesian interpretation of fuzzy logic has guided the ASTRA research.

## Certainty and Confidence

The Flight Mode Interpreter not only produces a qualitative description of the current state of the aircraft, but also provides two measures about that description – the *certainty* and the *confidence*. Both are measures in the range of [0, 1].

The certainty associated with each operational mode is the degree to which the current input variables match that mode using abductive reasoning [7]. The certainty is simply the degree of membership that a state vector has in the multidimensional fuzzy set for each mode. The multidimensional fuzzy modes are currently implemented by a composition of one-dimensional fuzzy sets defined in the domains of each input variable. For example, to determine if the airplane is currently in the TAKEOFF mode, the sensor readings for the altitude, thrust, rate of climb, etc. are independently calculated using the corresponding TAKEOFF fuzzy sets.

As an example, the degree of certainty that the aircraft is in the TAKEOFF mode is computed according to the Bayesian version of the fuzzy compositional rule of inference. Similarly, the confidence levels for the other modes are calculated and the decision of the current mode is taken to be the one with the maximum confidence.

Another calculation has proven useful in understanding the *confidence* associated with a particular flight mode decision. The confidence is calculated based on the flight modes with the highest and second highest certainty values. If $C_1$ is the certainty of the chosen mode, and $C_2$ is the next highest calculated certainty, the confidence of a decision is defined as

$$\text{Confidence}(C_1, C_2) = \frac{C_1 - C_2}{C_1}.$$

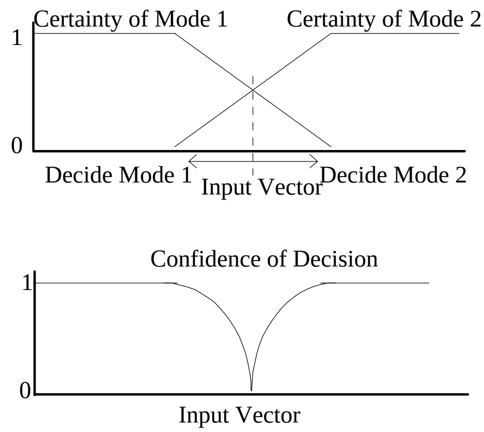


**Figure 2. Relationship between *certainty* and *confidence*.**

As the airplane transitions from one mode to another, the certainty values will inevitably decrease for the initial mode and increase for the mode being entered. The FMI will choose the mode with the highest certainty, and the confidence of that decision will decrease due to the ambiguity that exists in the transition.

## FMI Performance

The measure of the FMI's performance is how closely its mode decision matches the intended mode of the pilot. During testing of the FMI, the pilot indicates what mode best characterizes the current situation. The FMI should come reasonably close to selecting the same mode. The plot of Figure 3 is a good example of the FMI's ability to emulate what the pilot considers to be the modes for an entire flight from takeoff to touchdown. This plot is from a flight simulator for a Commander 700, a light, twin engine general aviation aircraft.

Notice that sometimes the computer's inference may slightly lead the pilot's stated mode (e.g., the CLIMBOUT to CRUISE transition). Other times the computer may lag in the inference (e.g., the CRUISE to INITIAL APPROACH transition). However, the FMI performance follows closely enough for the Pilot Advisor to give meaning and helpful messages through all seven stages of the flight.

## Concluding Remarks

Because of the high dimensionality of the flight mode interpretation problem, and because of the correlation inherent in the input variables, the authors have developed a new technique for expressing and calculating multidimensional fuzzy membership functions [8]. What has come to be known as *hypertrapezoidal fuzzy membership functions* shows promise as a new technology for development in the ASTRA system. Figure 4 is an example of four two-dimensional fuzzy sets defined on the state space of altitude and airspeed. The current FMI implementation relies on the composition of one-dimensional membership functions to approximate what are actually multidimensional relationships. Hypertrapezoidal membership functions are a way to

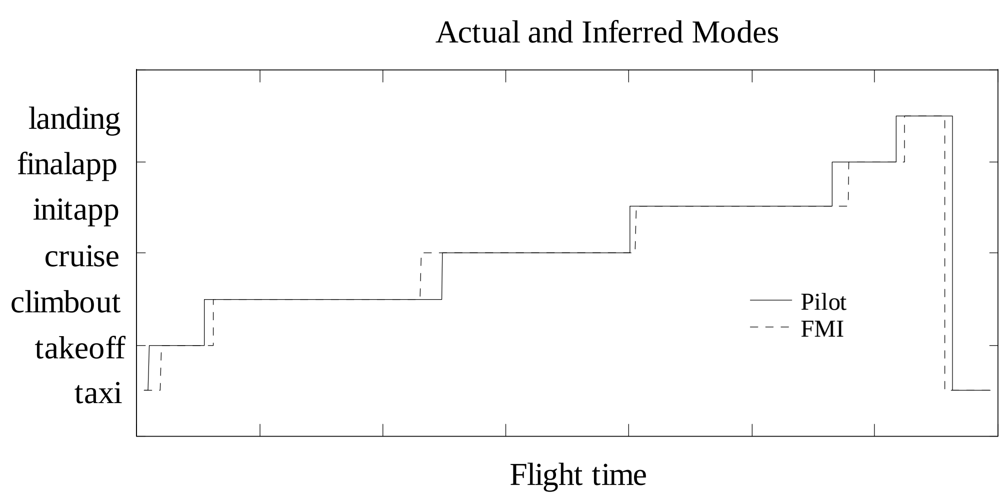


**Figure 3. FMI Performance for an entire flight.**

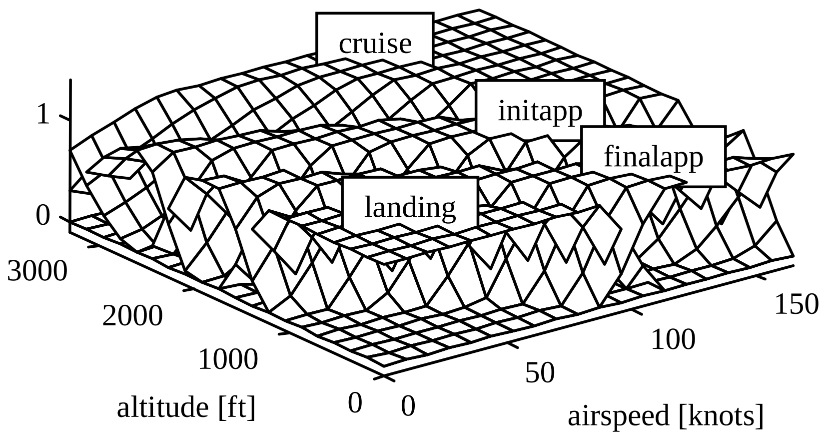


**Figure 4. Two-dimensional fuzzy membership functions.**

explicitly design correlated models of the flight modes.

While the new method is general for any number of dimensions, visualization is limited to plots of three dimensions – two input variables and the degree of membership. Eight-dimensional fuzzy sets are shown as they would be projected onto the domains of airspeed and altitude. Preliminary results show that multidimensional membership functions will be an efficient way to partition the input space into flight modes.

One promising aspect of the hypertrapezoidal approach is the ease with which training can be incorporated into the design of the fuzzy sets. The value of training methods for the fuzzy inference stage of ASTRA became obvious when the flight simulator’s model of the project’s Commander 700 aircraft was recently updated. The slight change in the aircraft model changed the aircraft state variables enough to produce a degradation in the FMI’s performance. The membership functions had to be manually re-tuned. Installing an ASTRA system on different aircraft (and perhaps even different configurations of the same aircraft) could be eased by an off-line training mechanism.

Another area of future research is “decision filtering”. Figure 5 shows an example of what the ASTRA team has termed “nervousness”. Notice how the interpreter’s decision oscillates back and forth between modes near the transitions. This translates into HUD symbology that comes and goes, and HDD messages that flicker off and on. Adjusting the fuzzy

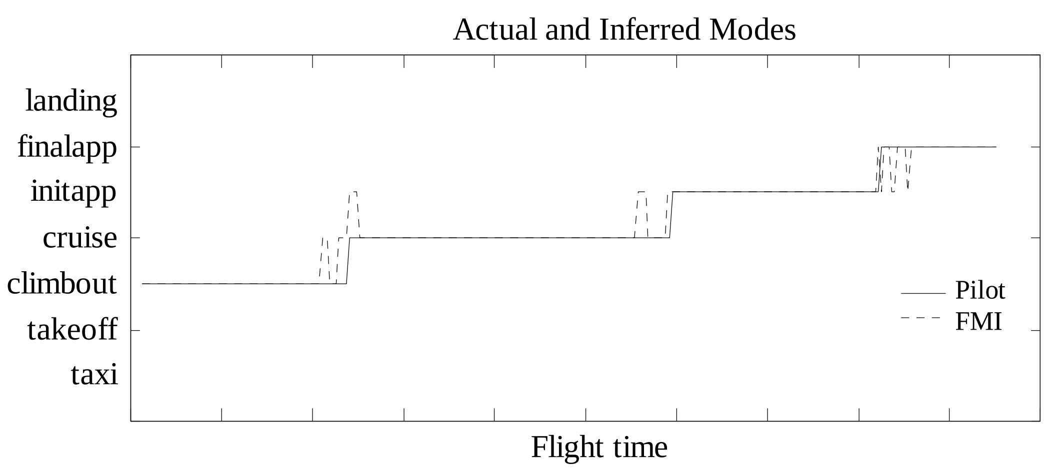


**Figure 5. Example of FMI’s “nervous” behavior near transitions.**

membership functions has smoothed much of the nervousness (the plot was generated using an old set of membership functions), but the FMI may still benefit from filtering either the certainty values or the inference itself.

The Aeronautical Safety and Training Rules Advisor is a step forward in smart-cockpit technology for GA aircraft that would not be feasible without the development of soft computing techniques.

## References

[1] J. H. Painter, “Knowledge-based Control”, *Proceedings of the 1992 IEEE Symposium on Computer Aided Control System Design*, Napa, CA, March 1992, pp. 138-147.

[2] E. Glass and J. H. Painter, “Discrete Fuzzy Control for Aircraft Flaps”, *Proceedings of the Second International Workshop on Industrial Applications of Fuzzy Control and Intelligent Systems*, College Station, Texas, 1992.

[3] L. A. Zadah, “Fuzzy Sets” *Information and Control*, June, 1965, pp. 338 - 353.

[4] T. J. Ross, *Fuzzy Logic with Engineering Applications*, McGRaw-Hill Inc., New York, 1995.

[5] W. Stallings, “Fuzzy Set Theory Versus Bayesian Statistics”, *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 7, No. 3, March 1977, pp. 216-219.

[6] J. H. Painter, "Fuzzy Decision and Control, The Bayes Context" *Proceedings of the 32nd IEEE Conference on Decision and Control*, San Antonio, Texas, December 15-17, 1993.

[7] E. Rich and K Knight, *Artificial Intelligence*, McGraw-Hill, Inc, New York, 1991.

[8] W. E. Kelly and J. H. Painter, "Hypertrapezoidal Fuzzy Membership Functions", *Proceedings of the Fifth IEEE International Conference on Fuzzy System*, New Orleans, September 8-11, 1996.