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Fuzzy Logic Based Intelligent Agents for Unmanned Combat Aerial Vehicle Control

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Introduction

Great strides have been made in remote-operated Unmanned Combat Aerial Vehicles (UCAVS), mostly in terms of ground strike capabilities. However when only millisecond timeframes are allowed for critical decisions to be made, any delay in communications and control severely weakens the combat capability of the system. While some proponents of autonomy focus on the ability to design aircraft that can perform maneuvers no human pilot would maintain consciousness through, or the simple fact those pilots' lives would no longer be at risk, these are not the only benefits these systems can provide. With an average human visual reaction time of 0.15 to 0.30 seconds, and an even longer time to compute optimal plans and coordinate them with squad mates; this offers a huge window of improvement that an Intelligent Agent (IA) can capitalize upon.

Even if the IAs were limited to keeping track of the same limited number of inputs and outputs that even expert pilots are capable of tracking, the ability to react and coordinate hundreds of times faster is a great advantage in terms of Course of Action (CoA) development. Certain methodologies however are not limited in terms of the number of dimensions that can be processed simultaneously during CoA development or refinement. During missions these systems can track, maintain time histories, and pull out useful knowledge of the opposing force from data such as hostile position, velocity, acceleration, angles and angular rates, maximum-g maneuvers, firing patterns, evasion maneuvers, formations and formation settling times, sensor utilization, estimated roles and tactics, and many others. As any entity learns additional information concerning a tactical advantage or disadvantage, this information can be immediately distributed and utilized.

This paints a picture of an extremely effective force, even if the capabilities of our platforms themselves did not improve. However there are many obstacles to this type of system. The main difficulties in the development of IAs for this type of problem are the vast number of inputs and outputs to be considered, as well as the uncertainty and randomness inherit in the problem and sensor noise and failure. There are a number of systems that can process tens to hundreds of inputs and outputs in faster than real-time; a requirement for training via a learning system. However, within the framework of UCAV control, none have been as resilient, adaptable, and robust as fuzzy logic based methodologies. The main difficulty in implementation of these technologies is the ability to verify and validate the IA, another unique strength of any fuzzy logic based IA which can be verified and validated utilizing formal methods. Safety specifications and operating doctrines can be guaranteed to be followed by the IA. Of course computing systems can crash and sensors can fail, though this is just as true for manned aircraft, and redundancies can be put in place.

The ability to lay out architecture for these types of problems is extremely simple for fuzzy logic based controllers compared to alternative methods. While we rely on a learning system to determine the ideal membership functions and if-then rules, the allocation and granularity of inputs and outputs, obviously optimal if-then rules, and any strategies gleaned from expert knowledge can still be hard-coded. Many research problems in the domain of UCAV autonomous control include next-gen technologies that have no established and well-vetted doctrine. However, many doctrines of air combat in general will still apply, and can be easily incorporated into fuzzy logic controllers.

One fuzzy methodology in particular, the Genetic Fuzzy Tree (GFT) got its start in a UCAV research problem funded by the Dayton Area Graduate Studies Institute [1]. The first GFT, LETHA or the Learning Enhanced Tactical Handling Algorithm, was tasked with the control of a squadron or squadrons of UCAVs equipped with next-gen defensive systems which had to determine optimal routes through highly-contested spaces, cope with communication losses, and in a time and safety optimal fashion, complete Suppression of Enemy Air Defences (SEAD) missions [2]. Utilizing this type of fuzzy control, LETHA was able to take in a significant number of inputs concerning the observed mission state and make high-performance real-time decisions that allowed even incredibly difficult missions to be completed safely.

Background

The UCAVs LETHA controls have a Laser Weapon System (LWS) and Self-Defense Missiles (SDMs) onboard. The SDMs are fire and forget missiles that can destroy enemy incoming missiles, whereas the LWS can burn through incoming ordinances over some duration, but has a maximum charge capacity and must recharge throughout the mission. The incoming missile's azimuth, distance, and guidance type determine the duration of the lase necessary to destroy it. Additionally, these defensive systems have a 90% probability of kill, meaning a flat 10% chance of failing to destroy their target is present.

A low-fidelity combat simulator was developed for this task. Enemies within include Surface to Air Missile sites (SAM sites), which fire groups of missiles nearly simultaneously at their target(s). Enemy air interceptors patrol within a given zone, and engage LETHA when approached. Lastly, Electronic WARfare (EWAR) stations block out all communications within a volumetric radius, and are usually located near enemy defenses and unarmed critical ground targets. The exact number and position of enemy aircraft is not known to LETHA in advance, but missile firings are detected immediately. An example mission layout is displayed below in Figure 1.

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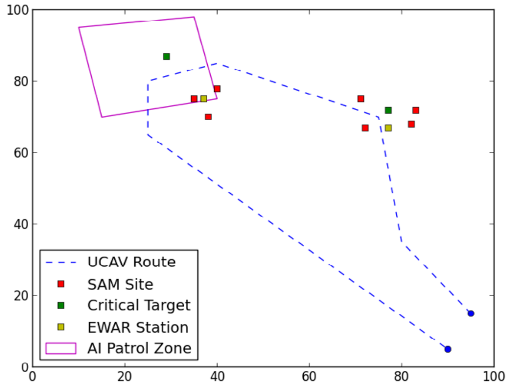

Figure 1: Example mission layout.

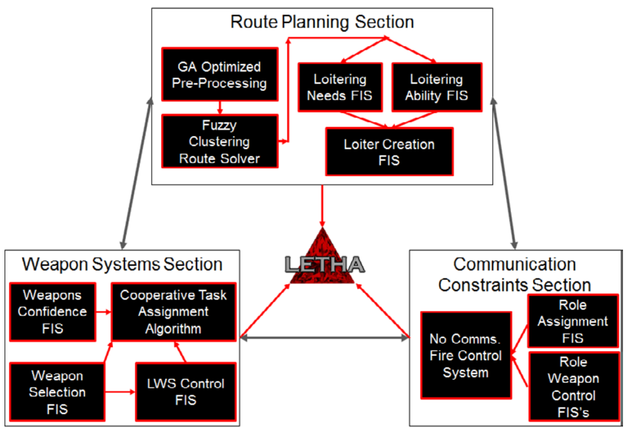

Figure 2: Visualization of LETHA's GFT.

The GFT methodlogy utilizes a series of Fuzzy Inference Systems (FISs) with varying degrees of connection between them. By breaking up the problem into many sub-decisions in a dynamic programming fashion, the solution space is significantly reduced. Unlike in Fuzzy Decision Trees or Fuzzy Networks, the nodes of a GFT are not individual components of FISs, but rather are unique FISs themselves [3-5].

Any coupling between inputs and outputs must be captured as best as possible. Thus, branches of the tree are utilized to capture inputs that are related, and connections between branches to certain FISs allow inputs to be considered in other FISs not directly within their same branch. As the number of if-then rules required for a fuzzy controller is exponential, based upon the number of membership functions of the inputs, this type of approach keeps the number of parameters as low as possible and allow a learning system to train the system. Figure 2 depicts a visualization of LETHA's GFT, with different branches governing routing, weapons, and communications.

Of note in Figure 2 is the ease in which other methods and algorithms can be incorporated into the system in different levels. A Cooperative Task Assignment Algorithm, Fuzzy Clustering Route Solver, and No Communications Fire Control System are directly incorporated [6-8]. This system requires a strong learning system, as the solution space is quite large. The entirety of the GFT needs to be trained simultaneously, to incorporate for coupling issues, and have performance converge. Initially, a heavily optimized Genetic Algorithm (GA) was utilized. The patent-pending EVE Learning System, developed by Psibernetix Inc., was also applied to LETHA and its performance compared. EVE is itself a GFT whose objective is to create and optimize other GFTs [9]. Through recursive self-application, EVE has been trained to learn how to better train other GFTs.

Results

LETHA learned over 6 training missions and 12 live missions in which post-trained, deterministic controllers were tested. The training portfolio focused on covering a wide variety of possible enemy layouts and capabilities, as well as testing LETHA in various states, such as having only the LWS and no SDMs. The live missions were developed such that a 90% survival rate was guaranteed possible if none of LETHA's countermeasures miss. Shown in table 1 are the success rates of trained LETHA's from both the initial optimized GA and EVE in the 12 live missions. Here mission success meant all enemy units destroyed and LETHA suffered no losses. EVE not only performed better, but also was over 10 times faster, able to train the system in under 2 hours on a laptop.

Multi-squad capabilities are highlighted in Figures 3 and 4. Figure 4 in particular displays the scalability of this approach, however this was not the largest case ran. LETHA has successfully completed difficult problems with 250,000 friendly aircraft. The main difficulty here is that the simulation is real-time and does not stop or slow down as LETHA processes CoAs. While this is a simplified, low-fidelity simulation environment, this was still accomplished on one laptop, displaying the extreme scalability and efficiency of this type of system [10].

Live Mission	Non-EVE GA Training	EVE-Optimized Training
1	93%	100%
2	98%	100%
3	96%	100%
4	99%	100%
5	100%	99%
6	91%	98%
7	100%	100%
8	92%	100%
9	94%	100%
10	100%	100%
11	97%	100%
12	94%	99%

Table 1: LETHA results in live missions.

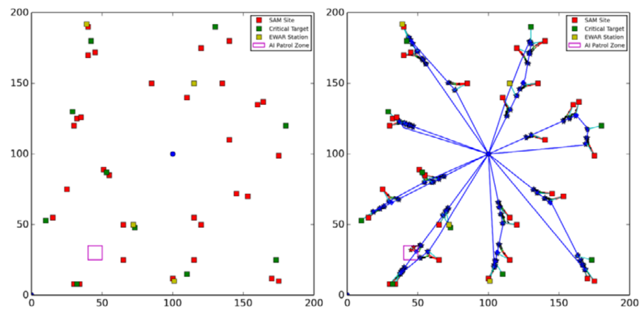

Figure 3: LETHA solution for 8-squadron problem.

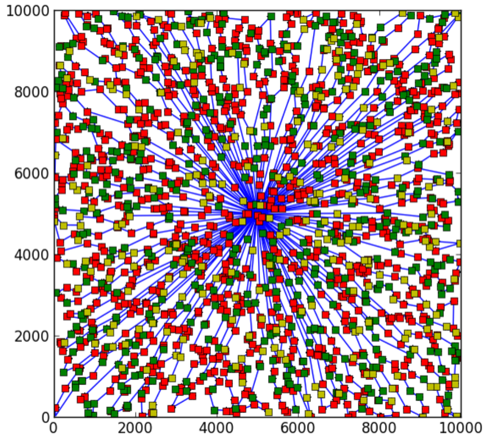

Figure 4: LETHA solution for 50-squadron problem.

Conclusion

Since the development of LETHA and EVE, these technologies have been applied to other UCAV problems. Psibernetix Inc. has "been tasked with the creation of an artificial intelligence for the research and development of increased autonomous capabilities to allow mixed combat teams of manned and unmanned air fighters to operate in highly contested environments" [11].

The capability ceiling and number of benefits that a GFT-based IA can bring to a problem such as this are quite high. If intel of the opposing force was imprecise or incorrect, adjustments to the knowledge of the hostiles' capabilities would be updated real-time as missions continued. This information could be broadcasted to other squadrons in the area, informing them that enemy tactics or platform capabilities are different than what was assumed. The IAs can keep better track of friendly assets, even in hectic and extremely stressful encounters, which aid in the ability to reduce the odds of a friendly fire, a significant concern especially in aerial combat.

They can be made impossible to be hacked or taken over, or if human in the loop is desired these risks can be severely mitigated. Our fighter pilots are extremely brave and well-trained individuals, however they are still human. If a near worst-case scenario occurs and the optimal plan includes a tactic with a very low survivability rate for a particular UCAV, the UCAV with the least resources remaining will happily choose to serve that role, without any anxiety, doubt, or adrenaline that may inhibit ideal decision-making. Upon taking even significant damage, the IA can calculate how to adjust control to either maintain flight, or perform the best possible landing maneuver. The IAs can be made to value the lives of civilians of an enemy territory more than their own or those of their squad mates. They do not require millions of tax-payers' dollars to train, hold no grudge, cannot suffer from PTSD, and are incapable of blinding hatred.

Outside the defense industry, the GFT methodology has found preliminary success in the financial and bioinformatics domain as well. The largest solution space EVE has trained a GFT over thus far has been 2.97*10^(961). For this problem, a standard genetic fuzzy system would have a solution space of 10^(3.464 × 10^(106)), or many times larger than a googolplex. Realistically, any type of big-data problem could benefit from the GFT, which provides the unique strengths of being a fuzzy-logic based intelligent system that is applicable to enormously complex problems.

Problems containing opposing forces, such as many of those in the defense domain, serve as excelling application areas for these types of systems. System noise and uncertainty are present, as well as a dynamic and often unpredictable enemy. These issues can be incredibly difficult for some methods of intelligent systems to cope with, as the enemy could actively try to act differently than the training set the system practiced over. Fuzzy logic has been shown to be extremely effective in the defense domain and will continue to push the boundaries of autonomous capabilities beyond their current state.

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