COMENIUS UNIVERSITY IN BRATISLAVA
FACULTY OF MATHEMATICS PHYSICS AND INFORMATICS

AN ADAPTIVE FUZZY INFERENCE IN PREDATOR-PREY PURSUIT GAME

Master thesis

2023 Valeriia Danina

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Master thesis

Study program:	Applied informatics
Branch of study:	Applied informatics
Department:	Department of Applied Informatics
Supervisor:	doc. RNDr. Dušan Guller, PhD.

Bratislava, 2023

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THESIS ASSIGNMENT

Name and Surname:	Valeriia Danina
Study programme:	Applied Computer Science (Single degree study, master II. deg., full time form)
Field of Study:	Computer Science
Type of Thesis:	Diploma Thesis
Language of Thesis:	English
Secondary language:	Slovak

Title: An adaptive fuzzy inference in predator-prey pursuit game

Annotation: Fuzzy expert systems (FES) belong to powerful AI instruments for emulating the process
of common/expert thinking, able to handle "soft" knowledge (uncertain, vague, imprecise, inconsistent, incoplete) in an efficient way. An interesting application of FES is simulation of multiple agents e.g. playing a predator-prey pursuit game. Each agent is equipped by its own base of heuristic fuzzy rules and performs reasonable multi-step inference of new "soft" facts, which ensures its adequate behaviour during a game. Such an agent's knowledge base can be advanced and refined in learning process using suitable AI-techniques.

Aim: The main aim is a design and development of a fuzzy expert system for multi-agent simulation of predator-prey pursuit game enabling implementation of suitable AI learning techniques.

Literature: SILER, W. - BUCKLEY, J. J. Fuzzy Expert Systems and Fuzzy Reasoning. Wiley. 2005.

LAW, M. A. - KELTON, M. D. Simulation Modeling and Analysis. McGraw-Hill Higher Education,
1999.

MILLINGON, I. Artificial Intelligence for Games. Morgan Kaufmann, 2006.

Keywords: fuzzy logic, expert system, multi-agent system, simulation

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Študijný odbor: informatika
Typ záverečnej práce: diplomová
Jazyk záverečnej práce: anglický
Sekundárny jazyk: slovenský

Názov: An adaptive fuzzy inference in predator-prey pursuit game
Adaptívna fuzzy inferencia v hre na predátorov a prenasledovanú korisť

Anotácia: Fuzzy expertné systémy (FES) patria k účinným UI nástrojom na emuláciu procesu bežného/expertného myslenia. Sú schopné pracovať so "soft" znalosťami (neurčitými, vágnymi, nepresnými, nekonzistentnými, neúplnými) efektívnym spôsobom. Zaujímavou aplikáciou FES je simulácia viacerých agentov napr. v hre na predátorov a prenasledovanú korisť. Každý agent je vybavený vlastnou bázou heuristických fuzzy pravidiel a vykonáva viackrokovú inferenciu nových "soft" faktov, ktorá zaisťuje jeho adekvátne správanie počas hry. Agentovú bázu znalostí môžeme vylepšovať a rafinovať v procese učenia využitím vhodných UI-techník.

Cieľ: Hlavným cieľom je návrh a vývoj fuzzy expertného systému pre multiagentovú simuláciu hry
na predátorov a prenasledovanú korisť, ktorá umožňuje implementovanie vhodných UI učiacich techník.

Literatúra: SILER, W. - BUCKLEY, J. J. Fuzzy Expert Systems and Fuzzy Reasoning. Wiley. 2005.

LAW, M. A. - KELTON, M. D. Simulation Modeling and Analysis. McGraw-Hill Higher Education,
1999.

MILLINGON, I. Artificial Intelligence for Games. Morgan Kaufmann, 2006.

Kľúčové slová: fuzzy logika, expertný systém, multiagentový systém, simulácia

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Spôsob sprístupnenia elektronickej verzie práce:
bez obmedzenia

Dátum zadania: 01.10.2019

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I hereby declare that I have written this thesis by myself, only with help of referenced literature, under the careful supervision of my thesis advisor.

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Bratislava, 2023 Valeriia Danina

Abstract

This master's thesis discusses the process of designing and developing a fuzzy expert system for multi-agent simulation of a predator-prey game that chases prey. To improve the accuracy of the system's results, additional training of the multi-agent system was performed using artificial intelligence training methods in the Matlab environment, which represent predators and prey as autonomous agents using their own rules to navigate in the "forest" environment depending on the situation around them and the provided rule system.

The expert system was designed and implemented in Matlab using the Fuzzy logic designer and the Simulink extension. The system uses a set of fuzzy rules that have knowledge about the world and decide which action is most appropriate to perform at a given moment. And Simulink allows you to model multi-agent systems in a closed environment for fixed periods of time.

Keywords: fuzzy logic, expert system, multiagent system, simulation

Abstrakt

Kľúčové slová: fuzzy logika, expertný systém, multiagentový systém, simulácia

Contents

Chapter 1

Introduction to fuzzy modeling

Fuzzy modeling is a special branch of mathematical modeling that has two goals: (i) to construct models based on information that can be given not only in numbers but also, imprecisely, usually in a form of expressions of natural language; (ii) to construct models with less computational demands, which are more robust, that is, little sensitive to changes in the input data.

In comparison with classical models, the fuzzy ones are closer to human way of thinking. For example, when processing images, classical methods work with single pixels. People, however, do not see pixels but larger and usually imprecisely delineated parts of the image. This is the main reason why it is so difficult to develop methods that are as powerful as the human eye. It happens quite often that some objective measure says that a given image is good, but the human eye sees it differently and says "no".

Fuzzy modeling is a group of special mathematical methods that make it possible to include in the model imprecise or vaguely formulated expert information that is often characterized using natural language. The developed models (we call them fuzzy models) are very successful because they provide solution in situations when traditional mathematical models fail—either due to their non-adequacy, or due to their inability to utilize the full available information.

Note that the idea to include imprecise information in our models contradicts to what has always been required: as high precision as possible. However, there is a good reason for doing it, we face a variance between relevance and precision. The so-called principle of incompatibility [13] says the following:

As a complexity of a system increases, our ability to make absolute, precise, and significant statements about the system's behavior reduces. At some moment, there will be a trade-off between precision and relevance. Increase in precision can be gained only through decrease in relevance; increase in relevance can be gained only through decrease in precision.

But at the same time, we argue that full precision is only our illusion and is not achievable, even in principle. Otherwise, we could obtain the same result independently on the chosen precision. But this is, in general, impossible.

The attempt to utilize the imprecise information in mathematical models led to the development of fuzzy modeling techniques. Recall that mathematical models manipulate with variables. In traditional models, values of the considered variable are taken from some set of numbers called a universe. Traditional mathematical models manipulate directly with its elements. In a fuzzy model, however, variables may represent fuzzy subsets of the universe. Hence, fuzzy models require partitioning of the universe into parts, for which it is specific that they need not be precisely formed and can overlap [7].

The most important tool in fuzzy modeling are fuzzy IF-THEN rules. These are special expressions, which characterize relations among parts of two or more universes. For example, let us consider an electric boiler and two universes: values of electric current (A) and temperature ($^\circ$ C). Then the following is a typical fuzzy IF-THEN rule: IF electric current is very strong, THEN temperature is high.

Benefits of a fuzzy (inference) systems.

- This system can handle all kinds of input, even if the information is not exact, unclear or has background noise.
- Making Fuzzy Logic Systems is simple and easy to understand.
- Fuzzy logic uses math ideas called set theory, and its reasoning is easy to understand.
- This helps solve difficult problems in many areas of life really well because it works like how a person thinks and makes choices.
- The computer rules can be explained using only a small amount of information, so it doesn't need much space to remember.

Not so good things about fuzzy (inference) system.

- Lots of scientists have ideas to fix a problem with fuzzy logic, which might make things unclear. We don't have a set way to solve a problem using fuzzy logic.
- It's usually hard or impossible to prove what makes it unique because we don't always have a mathematical explanation of how we do it.
- Fuzzy logic uses both exact and inexact information, which can lead to less accuracy.

Applications

- This thing helps spacecraft and satellites stay at the right height in outer space. People use it in the aerospace industry.
- This thing helps control how fast cars go and how traffic moves.
- It helps big companies make better decisions and assess individuals.
- This thing can be used in the chemical industry to control the pH, help with drying things, and with a process called chemical distillation.
- Fuzzy logic is a type of math that helps computers understand human language and do smart things. It's very useful in AI.
- Fuzzy logic is often used in modern control systems, like expert systems.
- Fuzzy Logic works like a person's decision-making process, but faster, and it is often used with Neural Networks. To make data more meaningful, we combine it and create partial truths using Fuzzy sets.

It should be emphasized that robustness is a typical feature not only of fuzzy control, but also of applications of fuzzy modeling in general. For example, when applying fuzzy modeling methods to character recognition, we need only few patterns, while in classical solutions, we need hundreds of them.

Chapter 2

Problem analysis

Many of the most interesting dynamics in nature have to do with interactions between organisms. These interactions are often subtle, indirect, and difficult to detect. Interactions in which one organism consumes all or part of another. This includes predator-prey, herbivore-plant, and parasite-host interactions. These linkages are the prime movers of energy through food chains. They are an important factor in the ecology of populations, determining the mortality of prey and the birth of new predators.

A connected system of predator and prey should cycle, according to mathematical models and common sense: predators grow in number when prey is abundant, predation reduces prey populations to low levels, predator numbers fall, and prey populations rise indefinitely. The Lotka-Volterra Model is one such model that mimics predator-prey interactions.

2.1 Classic version of predator-prey game

The classical predator-prey model is a mathematical model used to study the dynamics of populations in a predator-prey ecosystem. The model typically consists of a set of ordinary differential equations that describe the change in the population of two species, such as predators and prey, over time.

The model considers the rate of change in the prey population as a function of their own birth and death rates, and the rate of predation by the predators. Similarly, the rate of change in the predator population is a function of their own birth and death rates, and the rate of prey consumed.

The model assumes that the populations of both species are continuously growing or declining depending on the balance of birth and death rates, and the interaction between the two species. In particular, the prey population grows when there are few predators and declines when there are many, and the predator population declines when there is little prey and grows when there is plenty.

This model helps to understand the underlying mechanisms driving the fluctuations in populations of both species, and can be used to make predictions about future population dynamics based on changes in environmental conditions or other factors.

The Lotka-Volterra equations describe an ecological predator-prey (or parasite-host) model which assumes that, for a set of fixed positive constants a (the growth rate of prey), b (the rate at which predators destroy prey), r (the death rate of predators), and c (the rate at which predators increase by consuming prey). The following conditions will be held for our computer simulation model.

Let the prey population at time t be given by $y_1(t)$, and the predator population by $y_2(t)$. Assume that, in the absence of predators, the prey will grow exponentially according to $y_1' = a\ y_1$ for a certain $a > 0$. We also assume that the death rate of the prey due to interaction is proportional to $y_1(t)\ y_2(t)$, with a positive proportionality constant. So:
$y_1'(t) = a\ y_1(t) - b\ y_1(t)\ y_2(t)$

Without prey, predators will die exponentially according to $y_2'(t) = -r\ y_2\ dt$ for a certain $r > 0$. Their birth strongly depends on both population sizes, so we finally find for a certain $c > 0$:
$y_2'(t) = -r\ y_2(t) + c\ y_1(t)\ y_2(t)$

These equations lead to the following system of differential equations:

$$\begin{cases} y_1'(t) = a\ y_1(t) - b\ y_1(t)\ y_2(t) \\ y_2'(t) = -r\ y_2(t) + c\ y_1(t)\ y_2(t) \end{cases}$$

We see that both $(e^{at}, 0)$ and $(0, e^{-ct})$ are solutions of $(y_1(t), y_2(t))$. From this system, we find that for every solution we must have $y_1'(\frac{r}{y_1} - c) + y_2'(\frac{a}{y_2} - b) = 0$.

Integrating both sides give us:

$$r\ log\ y_1(t) - c\ y_1(t) + a\ log\ y_2(t)\ -\ b\ y_2(t) = constant.$$

The Lotka-Volterra equations are a pair of first-order, non-linear, differential equations that describe the dynamics of biological systems in which two species interact. The earliest predator-prey model based on sound mathematical principles forms the basis of many models used today in the analysis of population dynamics, the original form has problems [8].

The game is usually represented by a payoff matrix, where each entry represents the payoffs (or utilities) to the predator and prey given their current strategies. The strategies in this game correspond to the population sizes of the predator and prey, and the payoffs are determined by the underlying population dynamics described by the predator-prey model.

For example, suppose the prey population grows at a rate proportional to its size and the predator population grows at a rate proportional to the number of prey consumed. Then, the payoffs to the predator and prey can be represented as follows:

Predator Payoff $= (a - b) * P - c * Q$,

Prey Payoff $= d * Q - e * P$,

where P and Q are the population sizes of the predator and prey, respectively, a, b, c, d, and e are positive constants representing the growth and death rates of the populations, and the terms $(a - b) * P$ and $d * Q$ represent the intrinsic growth rates of the populations. The terms $-c * Q$ and $-e * P$ represent the costs of predation and being preyed upon, respectively.

This game has a unique Nash equilibrium, which is a state where neither player has an incentive to change its strategy, given the strategies of the other player. At the Nash equilibrium, the population sizes of both species are stable and remain constant over time.

The classical predator-prey game provides a framework for analyzing the interplay between the populations of predators and prey in an ecosystem, and can be used to understand the factors that influence the stability and persistence of both species.

2.2 Small modifications of predator-prey game

There are several ways in which the classical predator-prey game can be modified to better reflect the complexities of real-world ecosystems. Some common modifications include:

1. Adding multiple prey species: In many ecosystems, predators consume multiple prey species, and the interactions between these species can have important consequences for population dynamics. To reflect this, the predator-prey game can be extended to include multiple prey species, each with its own growth and death rates, and the predator's payoffs can depend on the populations of all the prey species.

2. Incorporating resource competition: In many ecosystems, prey species compete for limited resources, and this competition can affect both their growth and death rates. To incorporate this competition, the prey-prey interaction can be modeled as a separate game, and the payoffs to the prey species can depend on the populations of other prey species.

3. Allowing for adaptive behavior: In real-world ecosystems, the populations of both predators and prey can evolve, leading to changes in their behavior and interactions. To reflect this, the predator-prey game can be extended to allow for evolutionary dynamics, where the populations of both species can evolve to better adapt to their

environment.

4. Incorporating habitat destruction: Human activities, such as deforestation and urbanization, can significantly alter the habitats of both predators and prey, and this can affect their population dynamics. To reflect this, the predator-prey game can be extended to include a third player, representing the habitat, and the payoffs to the predator and prey can depend on the state of the habitat.

These modifications can provide a more accurate representation of real-world ecosystems, and help to shed light on the complex interactions between predators, prey, and their environment. However, they also introduce additional complexities and can make the analysis of the predator-prey game more challenging.

2.3 Introduction to the fuzzy logic

Fuzzy logic, a mathematical theory for uncertainty, was introduced by Zadeh in 1965 as an extension of boolean logic, based on the mathematical theory of fuzzy sets. Fuzzy logic allows for a condition to be in a state other than just true or false by introducing the concept of degree in the verification process. This enables the consideration of inaccuracies and uncertainties, giving reasoning a valuable degree of flexibility. One of the many benefits of fuzzy logic is its ability to formalize human reasoning through natural language-based rules. Fuzzy systems are designed to emulate human reasoning processes, and if-then rules are used to represent relationships explicitly.

2.3.1 Fuzzy sets

Fuzzy sets generalize the classical concept of a set. Their motivation stems from the following idea: If somebody wants us to specify a set of all speed values which can be referred as a high speed value. First we can say that the speed range for what we can specify as a high speed is between 130 and 480. So, we start with the set $U = [130, 480]$ (kph). In further reasoning, however, we will be confronted with insurmountable difficulties, namely, we find out that we are not able to specify high speed value precisely. For example, if we decide that the high speed is at least 140, then we can immediately ask: “What about the speed 139 kph?” We are not able to distinguish such speed difference by naked eye only. But, according to our decision, the first value is considering as a high speed value, and the second one is not. We arrive at clearly counterintuitive conclusion. Therefore, in a common practice, we cannot understand numbers to be fully precise but rather to be imprecise, for example, “approximately 150”. Alternatively, we can use vague linguistic expressions such as “slow” and “very fast”. [7] The general definition of a fuzzy set is the following.

Let U be a set called universe. A fuzzy set is a function

$$A : U \to [0, 1].$$

This function is also called a membership function of the fuzzy set A. If $u \in U$, then the number $A(u) \in [0, 1]$ is called a membership degree of u in the fuzzy set A.

2.3.2 Fuzzy operators

The notation and operations of fuzzy logic are based on classical logic and propositional calculus, a modern form of classical logic notation. In classical logic, propositions are either true or false, with nothing in between. It is often common to assign numerical values to the truth of propositions, where 1 means true and 0 means false. An important principle of classical logic is the Law of Excluded Middle, which states that a proposition must be either true or false, and the Law of Non-contradiction, which states that a proposition cannot be both true and false. A statement cannot be true and false at the same time.

The truth value of complex propositions is obtained by combining the truth values of the elemental propositions, which enter into the complex proposition. The most common operators are NOT, AND (A AND B is true if both A and B are true) and OR (A OR B is true if either A or B or both are true.)[9]

The evaluation of formulae A AND B and A OR B is shown in Table 2.1, a presentation is called truth table.

Table 2.1: Truth table for AND and OR logic operators

A	B	$A\ AND\ B$	$A\ OR\ B$
0	0	0	0
0	1	0	1
1	0	0	1
1	1	1	1

For all fuzzy operators,

$$NOT\ A = 1 - A$$

$A\ AND\ B$

Zadeh operator: $A\ AND\ B = min(A,\ B)$

Probabilistic operator, assuming independance: $A\ AND\ B = A * B$

Bounded difference operator: $A\ AND\ B = max(0, A + B - 1)$

$A\ OR\ B$

Zadeh operator: $A\ OR\ B = max(A, B)$

Probabilistic operator, assuming independance: $A\ OR\ B = A + B - A * B$

Bounded difference operator: $A\ OR\ B = min(1, A + B)$

2.3.3 Fuzzification

Fuzzification means to find grades of membership of linguistic values of a linguistic variable corresponding to an input number, scalar or fuzzy.

2.3.4 Defuzzification

At the end of an advanced rule-firing sequence in a fuzzy expert system, a fuzzy conclusion C is often reached. However, C is a linguistic variable with graded membership values, and we usually need to compute a single scalar that corresponds to these values. This is where defuzzification comes in – the process of converting C into a scalar that can be sent as a signal to the process in question, especially in fuzzy control. Defuzzification is more intricate than fuzzification, with multiple choices to be made and many methods proposed. In this article, we will highlight the essential areas where choices must be made and identify the most commonly used choices, rather than exploring every possibility. Assuming we know the grades of membership of the fuzzy set to be defuzzified, the first step in defuzzification is to decide how to modify the membership functions for linguistic values to reflect that each value probably has a different grade of membership. This modification involves ANDing the membership function $m(x, value)$ with $m(value, lvar)$, where $lvar$ is the linguistic variable of which value is a member, $m(x, value)$ is the membership of real number x in value, and $m(value, lvar)$ is the membership of value in $lvar$. The result of the modification is a new membership function for value called $m0(x, value)$.

The most common choices for the AND operator are the Zadehian min(A, B), often known as the Mamdani method because of its early successful use in process control by Mamdani (1976).

Next, the individual membership functions must be aggregated into a single membership function for the entire linguistic variable. Aggregation operators resemble t-conorms, but with fewer restrictions, the Zadehian max OR operator is frequently used.

In the last step, we find a single number compatible with the membership function and this number will be the output from this final step in the defuzzification process.[9]

The fuzzy set has a following form $A = \{a_1/u_1, ..., a_r/u_r\}$ defined on a finite universe U.[7]

Center of Gravity/Area defuzzification is the most often used method and is used for fuzzy approximation problems:

$$COG(A) = \frac{\sum_{k=1}^{r} A(u_k) \cdot u_k}{\sum_{k=1}^{r} A(u_k)}$$

Mean of maxima defuzzification is computationally simpler than COG:

$$MOM(A) = \frac{1}{r_{max}} \sum_{j=1}^{r_{max}} u_j^{max}$$

First of maxima and last of maxima defuzzifications are the simplest defuzzification methods:

$$FOM(A) = min\{u_j^{max} | j = 1, ..., r_{max}\},$$

$$LOM(A) = max\{u_j^{max} | j = 1, ..., r_{max}\}.$$

Center of sums defuzzification is a variant of COG. Let us assume that set a is a union of fuzzy sets

$$A = B_1 \cup ... \cup B_s.$$

$$COS(A) = \frac{\sum_{j=1}^{s} (\sum_{k=1}^{r} u_k \cdot B_j(u_k))}{\sum_{j=1}^{s} \sum_{k=1}^{r} B_j(u_k)}.$$

DEE fuzzification, it classifies a fuzzy set to be defuzzified into one of the three types—Z, M, and S:

$$DEE(A) = \begin{cases} LOM(A) & \text{if } A \text{ is of type } Z \\ MOM(A) & \text{if } A \text{ is of type } M \\ FOM(A) & \text{if } A \text{ is of type } S. \end{cases}$$

2.4 Adaptive neuro-fuzzy inference system (ANFIS)

An adaptive network is a multi-layer feedforward network in which each node performs a particular function (node function) on incoming signals as well as a set of parameters pertaining to this node. The nature of the node functions may vary from node to node, and the choice of each node function depends on the overall input-output function which the adaptive network is required to carry out.

ANFIS represent Sugeno-Takagi fuzzy models and uses a hybrid learning algorithm. It has five layers as shown in figure 2.1.

The first hidden layer is responsible for the mapping of the input variable relatively to each membership functions. The operator T-norm is applied in the second hidden layer to calculate the antecedents of the rules. The third hidden layer normalizes the rules strengths followed by the fourth hidden layer where the consequents of the rules are determined. The output layer calculates the global output as the summation of all the signals that arrive to this layer. ANFIS uses backpropagation learning to determine the input membership functions parameters and the least mean square method to determine the consequents parameters. Each step of the iterative learning algorithm has two parts. In the first part, the input patterns are propagated and the parameters of the consequents are calculated using the iterative minimum squared method algorithm, while the parameters of the premises are considered fixed. In the second part, the input patterns are propagated again and in each iteration, the learning algorithm backpropagation is used to modify the parameters of the premises, while the consequents remain fixed. [11]

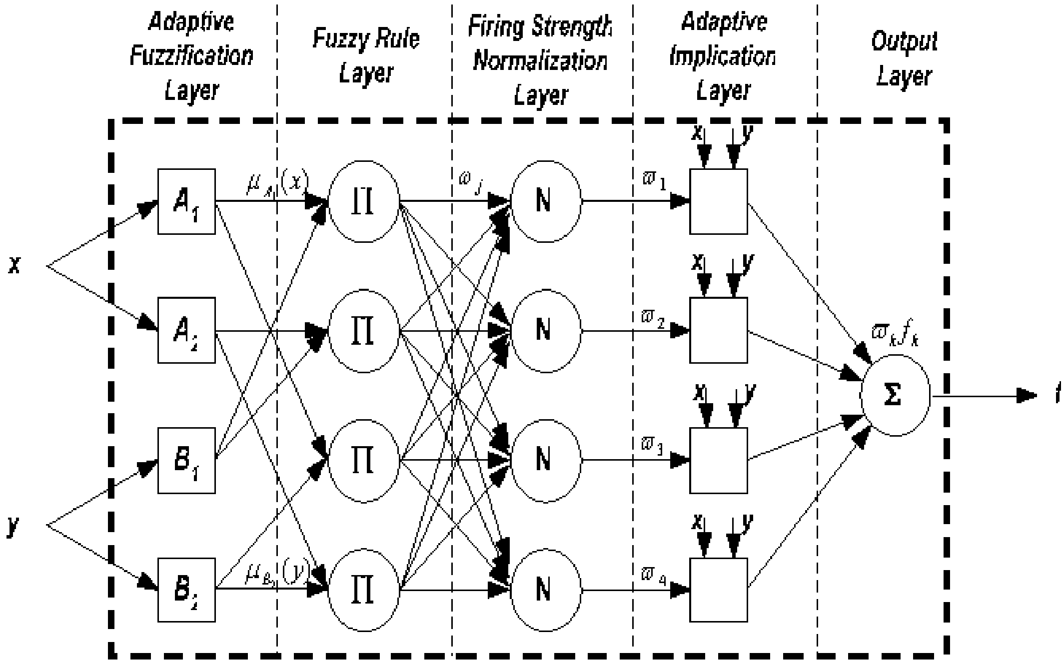

Figure 2.1: ANFIS architecture with two inputs, one outpur and four rules

2.5 Multiagent system

An agent is an autonomous computer system that functions on behalf of its owner or user. Unlike being told what to do, an agent can independently determine what actions it must take to meet its objectives. A multiagent system comprises several agents that interact with each other by exchanging messages through a network infrastructure. In the case of multiagent systems, each agent represents or acts on behalf of users or owners who may have different goals and motivations. Therefore, to interact successfully, agents must possess the necessary skills to collaborate, coordinate, and negotiate with each other, much like how we interact with people in our daily lives.

Multiagent systems are - by definition - a subclass of concurrent systems, and there are some in the distributed systems community who question whether multiagent systems are sufficiently different to 'standard' distributed/ concurrent systems to merit separate study.

In multiagent systems, however, there are two important twists to the concur - rent systems story. [12]

- First, because agents are assumed to be autonomous - capable of making independent decisions about what to do in order to satisfy their design objectives - it is generally assumed that the synchronization and coordination structures in a multiagent system are not hardwired in at design time, as they typically are in standard concurrent/distributed systems. We therefore need mechanisms that will allow agents to synchronize and coordinate their activities at run time.

- Second, the encounters that occur among computing elements in a multiagent system are economic encounters, in the sense that they are encounters between self-interested entities. In a classic distributed/concurrent system, all the computing elements are implicitly assumed to share a common goal (of making the overall system function correctly). In multiagent systems, it is assumed instead that agents are primarily concerned with their own welfare (although of course they will be acting on behalf of some user/owner).

2.6 Current overview of fuzzy modeling predator-prey game

Scientists use predator-prey models to study how animals that hunt (predators) and animals that are hunted (prey) interact in a certain environment. Fuzzy modeling is a way to study complicated things using fuzzy logic.

In a fuzzy game, the population dynamics of predators and prey are modeled using fuzzy logic. Fuzzy logic helps us understand better how predators and prey relate to each other. It does this by considering the fact that ecological systems are often uncertain and imprecise.

You can use a fuzzy inference system to model a game where a fuzzy predator chases a fuzzy prey. It has three parts: making things fuzzy, figuring out what to do, and making things clear again. Fuzzification is when we turn simple information like how many people live somewhere or things in the environment into fuzzy groups. Inference means using fuzzy rules to make predictions about how predators and prey populations will change. Defuzzification means changing the unclear results back into clear data.

Fuzzy modeling has been applied to predator-prey games in various ways to understand the behavior of the agents and to develop optimal strategies for managing populations in real-world scenarios. Here are some current overviews of fuzzy modeling predator-prey games:

Fuzzy logic-based predator-prey models: These models use fuzzy logic to develop rules for the agents' behavior based on their characteristics and the environment. The rules are defined using linguistic terms and fuzzy sets that represent the degree of membership of an agent in a particular category. These models have been used to simulate different scenarios and to evaluate the effectiveness of different strategies for managing predator and prey populations.

Fuzzy game theory-based predator-prey models: These models use fuzzy logic and game theory to analyze the behavior of the agents in predator-prey games. The models are based on the assumption that both predators and prey have incomplete information about the behavior of the other agents and are uncertain about the outcome of their actions. The models use fuzzy logic to represent the uncertainty and game theory to analyze the interactions between the agents.

Fuzzy reinforcement learning-based predator-prey models: These models use fuzzy logic and reinforcement learning to develop optimal strategies for the agents in predator-prey games. The models use fuzzy logic to represent the state of the environment and the actions of the agents and use reinforcement learning algorithms to learn the best actions to take in different situations. These models have been used to develop effective strategies for managing predator and prey populations in real-world scenarios.

Overall, fuzzy modeling can provide a more comprehensive and accurate representation of the complex dynamics between predators and prey in ecological systems. It can also be used to explore different scenarios and predict the outcomes of different management strategies.

2.7 A review of some recent modifications

There have been several recent modifications of fuzzy modeling predator-prey games to improve their accuracy and effectiveness. Here are some examples:

Hybrid fuzzy systems: Some researchers have combined fuzzy logic with other techniques such as neural networks or genetic algorithms to create hybrid fuzzy systems. These systems can improve the accuracy and robustness of the models by combining the strengths of different techniques.

Multi-objective optimization: Some recent models have used multi-objective optimization to develop strategies that balance multiple objectives, such as maximizing the predator's success rate while minimizing the impact on the prey population. These models can provide more realistic and sustainable solutions to managing predator and prey populations.

Multi objective optimization problem is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. Such problems can be found in various fields: product and process design, finance, aircraft design, the oil and gas industry, automobile design, or wherever optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover and is the most commonly used search techniques in computing to find exact or approximate solutions to such optimization and search problems.

In real world problems, parameters of a process are never precisely fixed to a definite value. Transients, noise, measurement errors, Instrument's least count etc makes it even more difficult to know their exact value at any time stamp. Even if externally regulated, parameters have some variability in their values. This variability has been continuously ignored by using mean/approximated/fixed value of the parameters, thus losing the precious information about the variability in the final optimized solution.

Dynamic models: Some researchers have developed dynamic fuzzy models that can adapt to changes in the environment and the behavior of the agents. These models can simulate more realistic scenarios and can be used to study the long-term effects of different management strategies.

Agent-based models: Some recent models have used agent-based modeling to simulate the behavior of individual agents in predator-prey games. These models can provide a more detailed understanding of the behavior of the agents and can be used to develop more precise management strategies.

Fuzzy decision-making: Some researchers have used fuzzy decision-making to develop strategies for managing predator and prey populations. These models use fuzzy logic to evaluate the effectiveness of different strategies and to select the best course of action based on the current state of the environment and the behavior of the agents.

Overall, these recent modifications of fuzzy modeling predator-prey games have improved the accuracy and effectiveness of the models and have provided new insights into the dynamics of predator-prey interactions. Further developments in fuzzy modeling techniques are likely to continue to improve our understanding of these complex systems and to provide more effective management strategies for predator and prey populations.

2.8 Matlab Fuzzy Logic Toolbox

Fuzzy Logic Toolbox provides a range of useful features for MATLAB users, including functions, apps, and a Simulink block for analyzing, designing, and simulating fuzzy logic systems. The product enables you to configure inputs, outputs, membership functions, and rules of both type-1 and type-2 fuzzy inference systems with ease. Additionally, automatic membership function and rule tuning is available to you. Evaluate the created fuzzy logic systems in MATLAB and Simulink, or utilize the fuzzy inference system as a support system to explain AI-based black-box models.[10]

Chapter 3

Design

Chapter 4

Implementation

Chapter 5

Results

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