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RESEARCH ARTICLE

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TAKAGI-SUGENO FUZZY MOTION CONTROLLER FOR DYNAMIC OBJECT TRACKING USING HETEROGENEOUS PARTICLE SWARM OPTIMIZATION ALGORITHM

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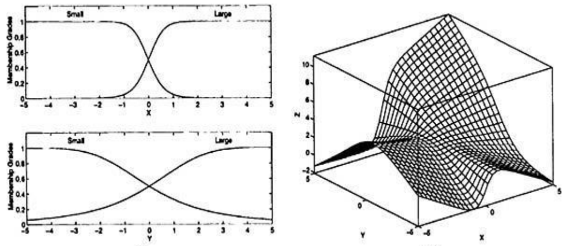
ABSTRACT

Object detection and tracking is an essential ingredient of any motion planning controller employed for mobile robot navigation.The particle swarm optimization (PSO) algorithm is extensively applied in the field. However, the classical PSO struggles from early convergence, and it is surrounded easily into local ideals, which will knowingly affect the perfect accuracy. To overawed these disadvantages, we have developed a new T–S fuzzy system parameters penetrating strategy called heterogeneous multi-swarm to enhance the penetrating performance. MsPSO groups the whole population into multiple cooperative sub-swarms, which perform different search behaviors for the potential solutions. In this paper, a non-linearidentification Takagi-Sugeno fuzzy motion controller has beendesigned to track the positions of a moving object with the mobileplatform. Experimental results show that MsPSO performs significantly better than old-style algorithms. With the improved MsPSO can generate a good fuzzy system model with high accuracy and strong generalization ability.

INTRODUCTION

Generally speaking, a T–S fuzzy model consists of several IF–THEN rules, which include the fuzzy antecedents and the mathematical function considered as the rule consequent parts. The task to construct a T–S fuzzy model can be divided into two steps: 1) extracting the fuzzy rules and 2) optimizing the parameters of the linear regression models. The main purpose of extracting fuzzy rules is to determine the model's structure, which depends on the clustering algorithm . The latter step can be achieved by optimization techniques, such as the least-squares method (LSM) , gradient descent , and genetic algorithm (GA). In the past two decades, researchers have found much success with T–S fuzzy modeling. In existing algorithms, the structures and the parameters of the fuzzy models are determined separately in different stages described earlier as opposed to simultaneously, where the model structures are first derived by clustering step, and then, the system parameters are optimized by evolutionary algorithms or heuristic methods. One disadvantage of these approaches is that it is difficult to guarantee that the obtained fuzzy models will have good performance because of the potential inconsistence between the two steps. In many cases, for example, the performance of a constructed fuzzy model can be further improved by tuning the membership functions and selecting suitable defuzzification methods. The advancements in wireless communication technologies enabled large scale wireless sensor networks (WSNs) deployment. Due to the feature of ease of deployment of sensor nodes, wireless sensor networks (WSNs) have a vast range of applications such as monitoring of environment and rescue missions. Wireless sensor network is composed of large number of sensor nodes. The event is sensed by the low power sensor node deployed in neighborhood and the sensed information is transmitted to a remote processing unit or base station.



(a) (b)

To deliver crucial information from the environment in real time it is impossible with wired sensor networks whereas wireless sensor networks are used for data collection and processing in real time from environment. The ambient conditions in the environment are measured by sensors and then measurements are processed in order to assess the situation accurately in area around the sensors. Over a large geographical area large numbers of sensor nodes are deployed for accurate monitoring. Due to the limited radio range of the sensor nodes the increase in network size increases coverage of area but data transmission i.e. communication to the base station (BS) is made possible with the help of intermediate nodes.

Depending on the different applications of wireless sensor networks they are either deployed manually or randomly. After being deployed either in a manual or random fashion, the sensor nodes self-organize themselves and start communication by sending the sensed data. These sensor networks are deployed at a great pace in the current world. Access to wireless sensor networks through internet is expected within 10-15 years. There is an interesting unlimited potential in this wireless technology with various application areas along with crisis management, transportation, military, medical, natural disaster, seismic sensing and environmental. There are two main applications of wireless sensor networks which can be categorized as: monitoring and tracking.

1.1 BACKGROUND

The use of different wireless devices like cell phones, GPS devices, laptops, RFID and other electronic devices have become more pervasive, cheaper and important in today's life. The demand for communication and networking among these various wireless devices has been increased for different applications. Wireless sensor networks from this point of view are the latest trend.

Ad Hoc Network (MANET) that is connected by wireless links is a self-configuring network of mobile nodes. The devices freely move in any direction and links among these devices are changed frequently. A cooperative network organized by collection of sensor nodes is a wireless sensor network. Both of these networks fall into the category of infrastructure less wireless networks as they do have any requirement regarding infrastructure during the deployment.

Wireless Local Area Networks (WLANs) and cellular networks fall into the other category of wireless networks that require infrastructure during their deployment.

1.2 PROBLEM DEFINITION

Routing of information differentiate these networks from other ad-hoc networks. The study of wireless sensor network is done by performing simulation that can help in better understanding of behavior of various routing protocols. Existing AODV and AODV with MsPSO algorithm are the routing protocols with performance metrics of packet delivery ratio, energy efficiency and throughput that are evaluated in NS2 in the network by increasing its size and then a comparison between the two is made to determine which protocol works best in the required application.

1.3 METHODOLOGY

1.3.1 WSN Architecture

In this step the required background information for the understanding of the subject of this project work is provided. Also a general understanding of the new emerging technologies from the wireless communication point of view is given in this step. It is simple to start with MANETs which are the base of WSN for the understanding of WSN.

1.3.2 Functionality of Routing Protocols

The explanation of the main characteristics and differences of the routing protocols and how they work for WSNs is presented in this step. This step includes how Selection of the path. Control messages etc.

1.3.3 Simulation Tool

NS-2.32 software is used in this study. It is mainly consists of two languages. They are OTCL and C++. The use of OTCL can be broken down into four major steps. Creation of nodes (modeling) is the first step, agent creation, application for the respective agents and finish procedure. The use of C++ is the back end process which supports for packet transmission.

1.3.4 Simulation

After detail discussion of routing protocols for WSN and necessary implementations, in the next step preparation of model for each routing protocol and analyzing its effect for critical condition monitoring application with the help of different parameters is done. These parameters are average packet delivery ratio, energy efficiency and throughput.

1.3.5 Analysis of Results

The results obtained for the selected routing protocols with the help of different parameters and scenarios from simulation are analyzed in this step.

WIRLESS SENSOR NETWORK

3.1 INTRODUCTION

Wireless sensor networks are composed of independent sensor nodes deployed in an area working collectively in order to monitor different environmental and physical conditions such as motion, temperature, pressure, vibration sound or pollutants. The main reason in the advancement of wireless sensor network was military applications in battlefields in the beginning but now the application area is extended to other fields including industrial monitoring, controlling of traffic and health monitoring. Different constraints such as size and cost results in constraints of energy, bandwidth, memory and computational speed of sensor nodes.

A wireless sensor node in a network consists of the following components:

- Microcontroller.
- Radio transceiver.
- Energy source (battery).

WSN have the following distinctive characteristics

They can be deployed on large scale. These networks are scalable; the only limitation is the bandwidth of gateway node.

Wireless sensor networks have the ability to deal with node failures. Another unique feature is the mobility of nodes. They have the ability to survive in different environmental surroundings. They have dynamic network topology. Further developments in this technology have led to integration of sensors, digital electronics and radio communications into a single integrated circuit (IC) package. Generally wireless sensor network have a base station that communicates through radio connection to other sensor nodes. The required data collected at sensor node is processed, compressed and sent to gateway directly or through other sensor nodes.

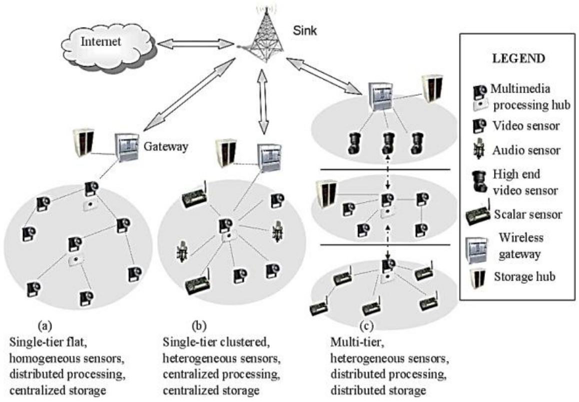


Fig 3.1 The Architecture of WSN network

3.2 SENSOR NODE ARCHITECTURE

A wireless sensor node is capable of gathering information from surroundings, processing and transmitting required data to other nodes in network. The sensed signal from the environment is analog which is then digitized by analog-to-digital converter which is then sent to microcontroller for further processing. While designing the hardware of any sensor node the main feature in consideration is the reduction of power consumption by the node. Most of the power consumption is by the radio subsystem of the sensing node. So the sending of required data over radio network is advantageous. An algorithm is required to program a sensing node so that it knows when to send data after event sensing in event driven based sensor model. Another important factor is the reduction of power consumption by the sensor which should be in consideration as well.

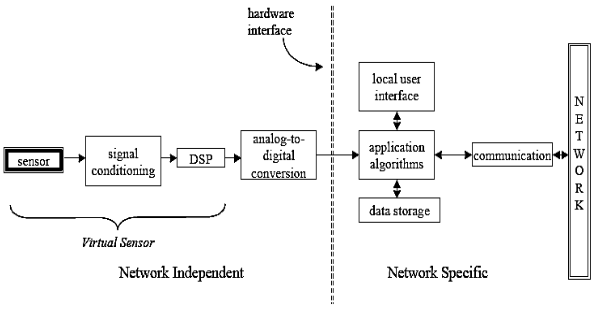


Fig 3.2 The Architecture of Sensor Network

During the designing of hardware of sensing node microprocessor should be allowed to control the power to different parts such as sensor, sensor signal conditioner and radio. The main functions of microprocessor among various functions are as follows

- Data collection management from other sensors.
- Power management functions are performed.
- Sensor data on physical radio layer interfacing.
- Radio network protocol management.

3.3 SENSOR NODE COMPONENTS

There are various sensor nodes having capabilities regarding power of microcontroller, radio and capacity of memory. Despite of the variances it can be said that there are four basic sub-systems of sensor nodes; computing subsystem, sensing subsystem, power subsystem and communication subsystem.

3.3.1 Controlling Component

In order to control the components of the sensor nodes and perform the required computations this subsystem is responsible for it. There are two sub-units, storage unit and processor unit. There are different operational modes of processors in sensor nodes. They are either Idle, Active or in Sleep modes. In order to preserve power this is important, so processor operates when required.

3.3.2 Communication Component

The sensor nodes due to this component interact with the base station and to the other nodes. Usually this subsystem is a radio of short range but other fields has also been explored like ultrasound, infrared communication and inductive fields. The advantage of radio frequency communication for sensor nodes is that it is not limited by line of sight and low- power radio transceivers with data-rates and ranges depending on the applications are easily implemented with the help of current technology.

3.3.3 Power Component

Power is supplied to sensor nodes by this sub-system in which a battery is contained. Every aspect of the network regarding communication algorithms, sensing devices, localization algorithms should be efficient in terms of energy usage because replacement or recharging of battery is unfeasible in case where large numbers of sensor nodes are deployed. For recharging of battery onsite a power generator should be included.

3.3.4 Sensing Component

In this sub-system the physical phenomena is converted to electrical signals by sensor transducers. So the outside world is linked to this subsystem. Sensors may have analog or digital output. There should be an analog to digital converter (ADC) incase if output is analog.

3.4 WSNs COMPARISON WITH MANETs

In general wireless communication is classified into two main categories as mentioned before. These two categories are infrastructure based and infrastructure less and further infrastructure less networks are divided into two groups which are WSNs and MANETs. The two networks are equivalent but built for different purposes. Both groups of wireless networks are self organizing networks where nodes are connected by wireless links, can move freely and the topology of the network changes constantly.

3.5 WSN APPLICATIONS

3.5.1 Monitoring of Area

The common application of WSNs is monitoring of area. The events occurring in the environment are monitored by the sensor nodes deployed in the region. Monitoring of area involves detecting enemy intrusion by a large number of sensor nodes deployed over a battlefield. The detected events are then reported to base station for some action.

3.5.2 Monitoring of Environment

A large scale wireless sensor networks are deployed for environmental monitoring including forest fire/flood detection, monitoring of the condition of soil and space exploration.

3.5.3 Applications in Commercial Area

Wireless Sensor Networks have a lot of applications concerning commercial are such as office/home smart environments, health applications, controlling of environment in buildings, monitoring of industrial plants.

3.5.4 Tracking Applications

In tracking area, WSN applications include targeting in intelligent ammunition and tracing of doctors and patients inside a hospital. A search and rescue system is designed using connectionless sensor based tracking system using witness (CenWits). Sensors with different radio frequencies and processing devices are used. This rescue system consists of mobile sensors, access points and GPS receivers. The search and rescue efforts are concentrated on an approximate small area with the help of CenWits.

Takagi–Sugeno Fuzzy Model: The T–S fuzzy model was proposed to describe a complicated nonlinear system, which decomposes the input space into several subspaces and each one is represented by a simple linear regression model. The typical T–S fuzzy rule is described as follows:

Ri: If *z*1 (*t*) is *F*1 *i*and if *z*2 (*t*) is *F*2 *i*and . . . and if *zn*(*t*) is *Fni*,then *x*˙ (*t*) = *Ax*(*t*). Given a nonlinear model

x˙ (*t*) = *f*(*x*(*t*)) (1)

there exists a model derived from T–S representation

x˙ (*t*) = *R*_*i*=1

hi(*z*(*t*))*Aix*(*t*) = *Azx*(*t*) (2)

where*f*(・) is a nonlinear function, *x* ∈R*n* is the state vector, *z*(*t*) is the premise variable, which is bounded and smooth in a compact set of the state space. In (2), the membership functions (MFs) *hi*(*z*) is given by *hi*(*z*) = *μi*(*z*)_*Ri*=1 *μi*(*z*)

(3) where*μi*(*z*)=_*nj*=1*Fji*(*zj*).Note that *hi*(・) satisfies_*Ri*=1 *hi*(・) = 1 and *hi*(・) _ 0. Given a system with the input vector **x** = [*x*1, *x*2, . . . ,*xN*], the output of the T–S fuzzy model can be calculated as follows:

_ *y* = _*Ri*=1 *hiyi*_*Ri*=1 *hi*(4)*yi*= *α*0

i+ *α*1 *i* *x*1 + ・ ・ ・+ *αNixN*(5) where *αji*is the consequent parameter of the *i*th output *yi*.*B. Particle Swarm Optimization Algorithm*Particle Swarm Optimization, originally developed by Kennedy and Eberhart [31], maintains a swarm of particles to search the search space for an optimal solution. Each particle represents a potential solution to an optimization problem.

Particle Swarm Optimization Algorithm:

Particle Swarm Optimization, originally developed by Kennedy and Eberhart [31], maintains a swarm of particles to search the search space for an optimal solution. Each particle represents a potential solution to an optimization problem. The *i*th particle is represented by **x***i* = (*xi*1, *xi*2 , ・ ・ ・. . . , *xiD*) in *D*-dimensional space, and its velocity is **v***i* = (*vi*1, *vi*2, . . . ,*viD*). Each particle will dynamically adjust its trajectory based on its historical best position (**p***i*) and the best position (**g**best) discovered by the whole swarm during the search process. The position and velocity of the *i*th particle are updated according to the following equations:

MULTISWARM PARTICLE SWARM OPTIMIZATION ALGORITHM

Ever since PSO was introduced, many researchers have focused on improving the algorithm. According to the update rules in the classical PSO algorithm, all particles are attracted by both the individual best position and the global best position. If the particles converge at a high speed, they will always shrink toward local regions within a few generations. This phenomenon leads to similar search behavior among the particles and the loss of diversity in the swarm. If the particles are trapped in local regions, they will not be able to jump out due to their homogeneous search behavior and the absence of exploration abilities. To improve the performance of PSO, the particles should be able to adaptively changing their original trajectories to explore new search space.

In this study, we propose a new multi swarm particle swarm optimization algorithm denoted as MsPSO to improve the performance of constructing the T–S fuzzy system. MsPSO separates the whole swarm into four sub swarms that can perform heterogeneous search but share information among each other, which is important to explore a larger space where the optimal model structure and parameter values potentially locate.

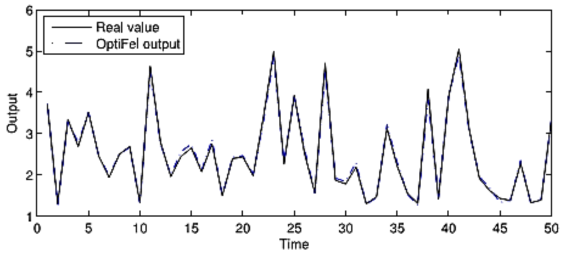
General Concept of Multi swarm Particle Swarm Optimization Algorithm

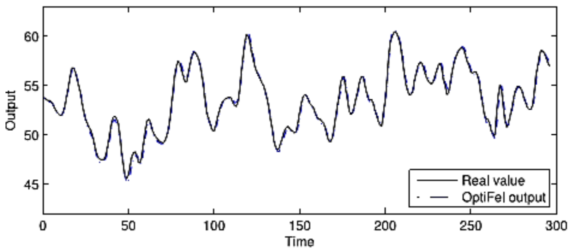
The proposed MsPSO algorithm is a heterogeneous search approach based on four subswarms. Among the four subswarms, we define two subswarms as the basic subswarms for exploitation search. The other two subswarms are the adaptive sub swarm and the exploration sub swarm, respectively. The adaptive sub swarm uses the information from the basic subswarms to adjust the flight trajectory adaptively, while the exploration sub swarm utilizes the flight direction information of the other subswarms to develop the unknown region. Accordingly, the PSO updating rules are modified to accommodate the designed multiple swarm concept. In MsPSO, we design three update rules to search the new areas according to the differences among the subswarms. Additional design involves the information exchange based on the useful knowledge of the velocities, the positions and the fitness values of particles in different subswarms. Based on the design of different multiple swarms and the cooperative heterogeneous search mechanisms, MsPSO can achieve a good balance between the local search and the global exploration. The cooperation and communication model among the subswarms, as shown in, is used to update fitness values and maintains MsPSO to share information among different subswarms. Meanwhile, it also shows the general concept of the cooperative relationship among the subswarms. One can obtain the basic idea of MsPSO—all subswarms contribute to the global exploitation and share the information with each other. For example, in sub swarm S_3, the particles use the messages of the velocities and fitness values from the particles in the basic subswarmsS_1 and S_2 to refresh their positions and velocities. Based on this information sharing mechanism, the particles in each sub swarm can learn from others and fully enhance their search abilities

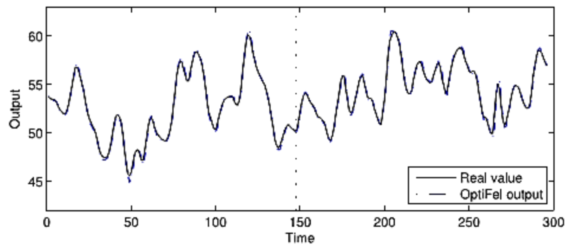
OPTIFEL FUZZY MODELING METHOD

This section presents the framework of the designed OptiFel method for the identification of a T–S fuzzy model and its applications for predictions. The structure and the parameters of a T–S fuzzy model are all encoded in a particle, which is used in a search problem. The details are presented in the following sections.

In the proposed method, the significance of suitable parameters is obvious. The parameters of a T–S fuzzy model are represented as a particle, which is defined as a vector consisting of the parameters. Let c_{ji}andσ_{ij}be the center of the dataset and the width of the fuzzy set, respectively. For a dataset with N inputs, we can calculate $F_{ij}(u_{ji})$ according to the Gaussian function

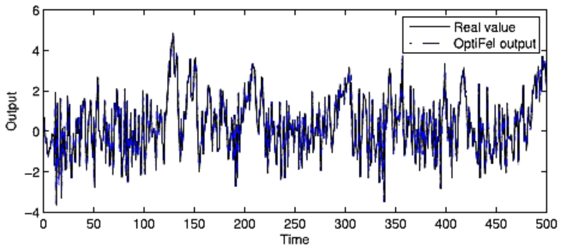






Conclusion

In this study, we proposed a new optimization-based data driven approach (OptiFel) to identify the T–S fuzzy system, where we designed a novel heterogeneous multiswarm particle swarm algorithm (MsPSO) for the optimization task. In the proposed OptiFel, the structures and the parameters of T–S fuzzy models are encoded as particles, and each particle represents a potential fuzzy model. This scheme has the merit of simultaneously obtaining all the model structures and parameters and reduces the inconsistence in the traditional two-stage identification process. In the MsPSO algorithm, the population is grouped into four subswarms to maintain heterogeneous search strategies. The information sharing mechanism not only gathers the useful messages from each sub swarm, but also contributes to the cooperation and potential search abilities. We have also theoretically proven that all the subswarms in MsPSO can converge to their own stable equilibrium points. The heterogeneous search engine implemented in



MsPSO is particularly useful for finding the optimal solutions with regard to a complex particle encoded by both the model structures and parameters. The experimental results demonstrate that OptiFel is able to generate efficient and robust T–F fuzzy model with better generalization ability.

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