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Multimodal Transport Path Planning Based on Multilateration (MLAT) System Using a Pulse Neural Network Model

Tongjuan Zhao[a,b,*], Jiuhe Wang[a]

[a] *Yanshan University, Qinhuangdao, 066004,China*

[b] *Qinhuangdao Institute of Technology, Qinhuangdao, 066004,China*

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ABSTRACT

This paper presents multilateration system for monitoring and scene surveillance. Multilateration (MLAT) system acquires the position of target mainly by the time-difference-of-arrival (TDOA) at the different ground stations. The mathematical modeling of the aircraft and vehicle in the MLAT system is carried out, and the shortest path planning problem is realized. The MLAT system improves the monitoring precision to provide security for real-time collision-free path planning of multimodal transport choice in stationary or non-stationary environments using modified pulse-coupled neural network (MPCNN) model. The proposed neural network is topologically organized with only local lateral connections among neurons. It works in dynamic environments and requires no prior knowledge of transport model. In the process of path planning of based on MLAT system, The transport between start to target with neurons like the propagation of a wave, which the target neuron fires first, and then the firing event spreads out, through the lateral connections among the neurons, then accurately record the excitation time of each neuron. The real time optimal path is the parent sequence from the starting neuron to the target neuron. In the static and dynamic conditions, an algorithm for generating wave is proposed. The number of propagation in the network is proportional to the connection intensity between the neurons. Therefore, the generated path is always the shortest path of the global. In addition, each neuron in the model can propagate the ignition event to adjacent neurons without any comparison calculation. The effectiveness and effectiveness of the proposed method are verified by simulation and comparative study.

1. Introduction

The multilateration(MLAT) system is a promising airport scene monitoring technology which compared with the traditional PSR and SSR surveillance, positioning accuracy, low cost and easy to install. The accuracy of aircraft and surface vehicles detection, identification, tracking, and communication is gradually increased by the use of multilateration systems. MLAT system has been successfully applied in many large international airports and becomes core technology in the advanced scene activity guidance and control system (A-SMGCS) proposed by international civil aviation organization (ICAO).

Nowadays, MLAT system based on ADS-B standard is a feasible option to be used in the air traffic control (ATC). ADS-B (automatic-dependent-surveillance-broadcast) is a surveillance system placed in aircraft that periodically transmits state vector estimates and other information to air traffic control centers and other nearby aircraft. It is assumed that the aircraft and surface vehicles are equipped with an ADS-B transponder, and it continually transmits the ADS-B signal at 1090 MHz every second. The structure of MLAT system is shown as Fig.1. MLAT system calculates a more accurate position based on the ground stations receiving the ADS-B signals by TDOA/TOA theory. Each ground station of MLAT system needs to preserve a higher time synchronization to reduce the time measurement error. It is necessary that all the ADS-B receivers are synchronized by a common GPS/rubidium clock standard to assist in the time synchronous capture of the ADS-B frames. The ADS-B signals are digitally processed by the ground stations to the central processing facility of MLAT system, and the positioning of the target is accomplished by the TDOA measurements value processing.

In this paper, the paths planning of aircraft and vehicles in airport scene are studied using neural network based on MLAT system. As a result, shortest problem has gotten the attention of multimodal transport, traffic engineers and other researchers. These techniques

* Corresponding author.
E-mail addresses: ztj2124@163.com (Z. Zhao)

include time series analysis, Bayesian networks, neural networks (NNs), fuzzy NNs, nonparametric regression (NP), and intelligence computation[1, 2].

Many scholars have proposed algorithms to solve this kind of problem[3, 4]. Liu investigated the solution algorithms for the multi-criteria multi-modal shortest path problem (M-SPP), which belongs to the set of problems known as NP-hard[5]. Lozano considered a label correcting approach to find the shortest viable hyper path from an origin to a destination, for different values of the upper limit of modal transfers [6, 7]. Dib have shown that the success rate of approach in terms of converging to optimum/near optimum solutions is highly better than a pure GA[8].

The remainder of this paper is organized as follows. In the second section of the MLAT system theory. The third chapter proposes the multimodal transport. The fourth section describes a path planning algorithm based on PCNN. The simulation results are given in section V and the conclusion is given in the end.

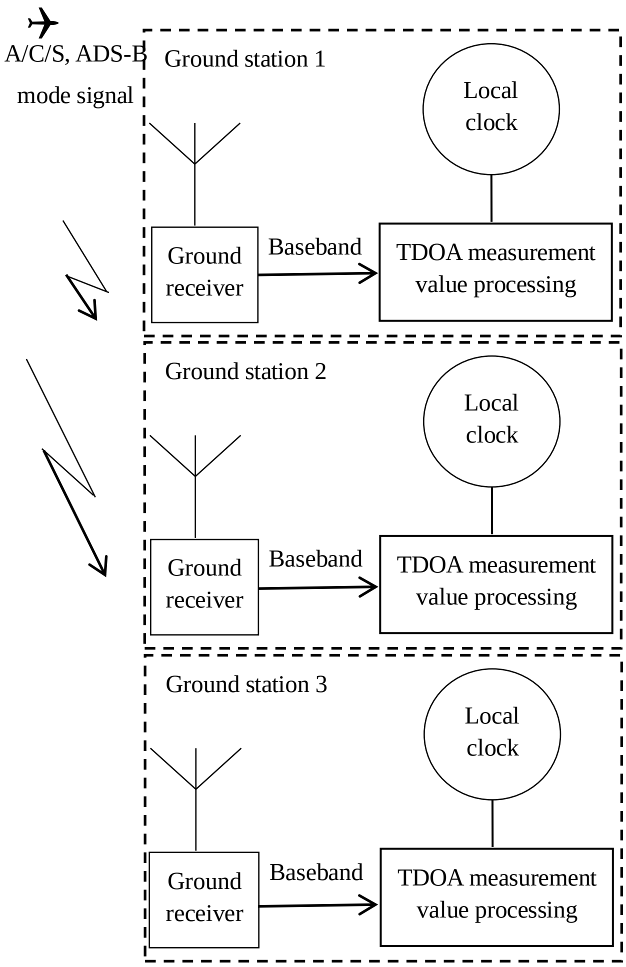

Fig.1 The structure of MLAT system

2. Multilateration technology theory

2.1 fundamental theory for MLAT system

MLAT systems are basically distributed surveillance and identification systems which are both short range and wide area for airport. In MLAT systems, a number of ground stations or "sensor" stations are placed in some strategic locations around the airport to make up a MLAT system network as Fig 2. State of the MLAT systems require high band-width communication lines for the correlation of signals from ground stations. The method of calculating the target position based on the TDOA principle is usually used. Furthermore, the local clocks of the ground stations must be synchronized with a very high precision to make the arrival time difference more accurate to reduce TDOA measurement error. The theory for TDOA principle is as Fig.3.

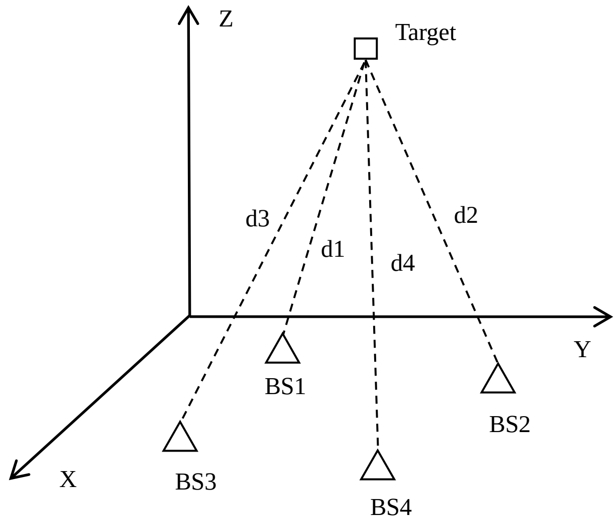

Fig.2 The schematic diagram for MLAT system

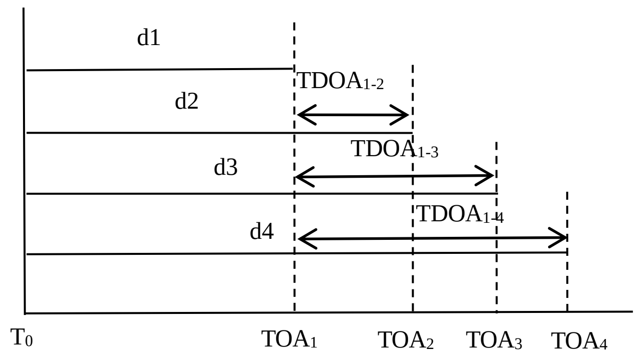

Fig.3 The theory for TDOA principle

2.2 Mathematical model for MLAT system

The TDOA technique is also called hyperbolic positioning where the target is visible to perform intersection of many hyperbolic surfaces. The coordinates of two ground stations are known as (x_1, y_1)、(x_2, y_2) , Suppose that the target's coordinate is (x, y) that is unknown. The time difference of signal to the two ground stations is Δt_1. According to the principle of TDOA, set up the following mathematical model:

$$\Delta t_1 \cdot c = \sqrt{(x-x_1)^2+(y-y_1)^2} - \sqrt{(x-x_2)^2+(y-y_2)^2} \quad (1)$$

where c is the velocity of light. The upper type expresses that the target position is on one of the hyperbola. The MLAT system generally includes at least four ground base stations, and there are three groups of time difference, and the intersection point of the curve represents the target position as follows.

$$\begin{cases} \Delta t_1 \cdot c = \sqrt{(x-x_1)^2+(y-y_1)^2+(z-z_1)^2} - \sqrt{(x-x_2)^2+(y-y_2)^2+(z-z_2)^2} \\ \Delta t_2 \cdot c = \sqrt{(x-x_1)^2+(y-y_1)^2+(z-z_1)^2} - \sqrt{(x-x_3)^2+(y-y_3)^2+(z-z_3)^2} \\ \Delta t_3 \cdot c = \sqrt{(x-x_1)^2+(y-y_1)^2+(z-z_1)^2} - \sqrt{(x-x_4)^2+(y-y_4)^2+(z-z_4)^2} \end{cases} \quad (2)$$

In the three-dimensional space, the MLAT system is used to locate the target, and the intersection point represents the target position, as shown in the Fig.4..

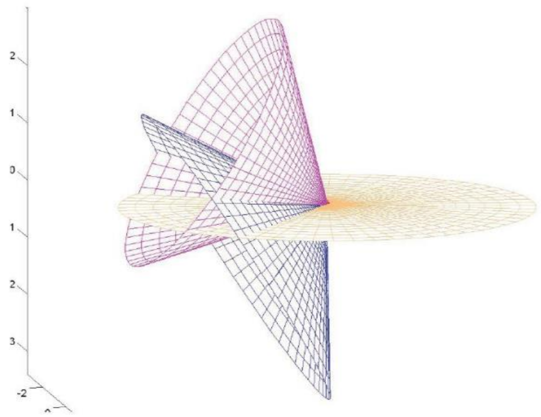

Fig.4 Three curves fix one point in 3D space

3. The theory of multimodal transport

For the transport from starting point S to the destination E, there exist some nodes in transport process as shown in the Fig.5. Assume the cargo would be transported through three cities, and every city has some three to four points which indicate the transport site, where nodes 11,12,13 mean the different transport site in the first city, nodes 21,22,23,24 mean the different transport site in the second city, nodes 31,32,33 mean the different transport site in the third city. Every line in the Fig.5 means the transport format between different site, including the different site in the same city. Such as the node 21 means the park in city 2, then the cargo can be transported by truck from the city 2 to node 31 which means the airport of city 3 through the line between node 11 to node 31, and also to node 32 which airport in city 3. Each site called neurons, connection between its known as the weights of neural network, the weight can be expressed as path or cost.

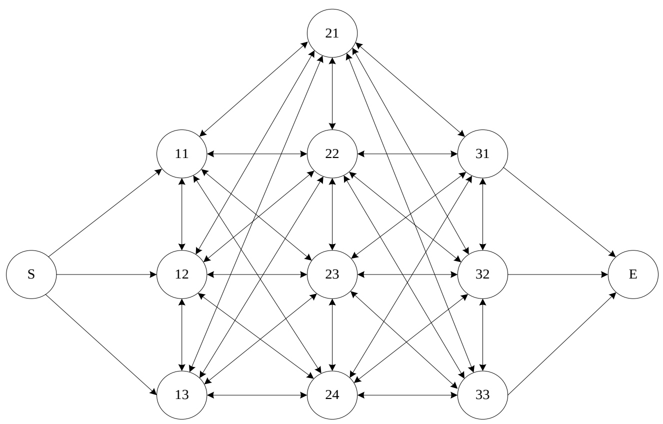

Fig.5. Multimodal transport

The key issue is the time and cost in multimodal transport, therefore in the transport process the weight transport neural networks is proposed which contain time and cost.

$$w_{ij} = f_{i,j}(T, C) \quad (3)$$

where T, C indicate the transport time and cost from the i to j. Therefore, the multimodal transport problem is transform into the shortest path planning. A modified pulse neural network can be used to realize the shortest path planning. A typical neuron of PCNN consists of three parts: the receptive fields, the modulation fields, and the pulse generator. The neuron receives input signals from other neurons and external sources through the receptive fields. The receptive fields can be divided into two channels: one is the feeding inputs and the other is the linking inputs. The modulation fields generate the internal activity of the neuron. The pulse generator receives the result of total internal activity and determines the firing events.

If internal activity is greater than the threshold, the output of neuron turns into 1, and the neuron fires, then the output feedbacks to make threshold rise over internal activity immediately, then the output of neuron turn into 0. Thus it produces a pulse output. It is clear that the pulse generator is responsible for the modeling of the refractory period.

4. PCNN Model for path planning and analysis

In this section, a modified PCNN is proposed to examine the path planning process. In addition, the architecture and variables are defined and used in this section.

4.1 Network Architecture

In the proposed PCNN model, each neuron i, $i, j = 1, 2, \ldots, N$ has one output Y_j.

$$Y_j(t) = Step(x_{ij}(t) - \theta_{ij}(t)) = \begin{cases} 1, & if \ \ x_{ij}(t) \geq \theta_{ij}(t) \\ 0, & otherwise \end{cases} \quad (4)$$

where $x_{ij}(t)$ and $\theta_{ij}(t)$ are the internal activity and threshold function, respectively, t is the time, N and is the total number of neurons.

The threshold function of neuron ij can be expressed as

$$\theta_{ij}(t) = \exp\left(w_{ij}\right) \quad (5)$$

for all $i = 1, 2, \ldots, N$, where w_{ij} is positive constants.

The internal activity x_{ij} of neuron ij determines the firing events. It can be determined by

$$x_{ij} = \begin{cases} 0 & 0 \leq t < t^i_{fire} \\ e^{t - t^i_{fire}} & t^i_{fire} \leq t < t^j_{fire} \\ 0 & t \geq t^j_{fire} \end{cases} \quad (6)$$

where t^i_{fire} is the time of the neuron y_i fired, and determined by the neuron x_{ki}.

4.2 Algorithm of Neural Networks

Before discussing the model, some notations and definitions about neuron firing and the firing time are defined as follows.

Definition 1: The fire time of the output of neuron i is definite as following:

$$t_{fire}^{i}=\left\{\min(t)\middle|x_{ki}(t)\geq\theta_{ki}(t),k\in\{1,2,3\cdots\}\right\} \quad (7)$$

Then the output of neuron i at time is represented by $Y_i(t)$ such that

$$Y_j(t)=\begin{cases}0, & t<t_{fire}^{j}\\ 1, & t\geq t_{fire}^{j}\end{cases} \quad (8)$$

where t_{fire}^{i} is the time at which output neuron i fires, after neuron $Y_j(t)$ fired, the neuron which connected directly with neuron $Y_j(t)$ is work as Definition 2.

Definition 2: Dynamic neuron ji is represented by $x_{ji}(t)$ such that

$$x_{ji}(t)\triangleq\begin{cases}x_{ji}=0, & t<t_{fire}^{j}\\ \dot{x}_{ji}=x_{ji}, & t_{fire}^{j}\leq t\leq t_{fire}^{i}\\ x_{ji}=0, & t>t_{fire}^{i}\end{cases} \quad (9)$$

where t_{fire}^{i} is the time at which neuron i fires.

For any given neuron $Y(i)$, after the output of neuron $Y(i)$ fires, its neighbor neurons x_{ij} are ready to fire and the firing time of this neuron is denoted as t_{fire}^{i}. A neuron $Y(j)$ will fire only if some neuron x_{ij} in its neighbor set fires. And then the neuron $Y(i)$ is said to be the parent of $Y(j), i=R_P^j$, and the firing time of neuron $Y(j)$ is denoted as t_{fire}^{j}. If another neuron in the same neighborhood fires and if it can make neuron $Y(i)$ fires early, then it will become the new parent of neuron $Y(i)$.

4.3 Theoretical analysis of the model

Theorem 1: For any given neuron i ,if $R_P^i=j$ and t satisfying.

$$\begin{cases}t_{fire}^{R_i^P}\leq t\leq t_{fire}^{R_i^P}+\ln(\theta_{ji})\\ \theta_{ji}(t)=\exp(w_{ji})\end{cases} \quad (10)$$

where θ_{ji} is the linking strength from i to j , the wave propagate process is work to the neuron j .

Proof: It is clear that at time $t=t_{fire}^{R_i^P}$. Under the stimulation of neuron R_i^P ,

$$x_{ji}=0 \quad (11)$$

For $t>t_{fire}^{R_i^P}$. Thus

$$\theta_{ji}(t)=\exp[w_{ji}] \quad (12)$$

Then, from Definition 1, we have

$$t_{fire}^{i}=t_{fire}^{R_i^P}+w_{ji} \quad (13)$$

This completes the proof of Theorem 1.

From Theorem1 it can be drawn that the wave propagates process is work from neuron j to the neuron i .

Theorem 2: Assume that there is a neuron which is the target that fired first, and then the wave propagates to neuron i and neuron j , the two paths are $PATH_i$ and $PATH_j$. The time that the firing wave propagates to i is T_i along $PATH_i$ and to j is T_j along $PATH_j$. If Theorem 1 hold, then

$$T_i\geq T_i\Leftrightarrow L(PATH_i)\geq L(PATH_j) \quad (14)$$

where $L(PATH_i)$ and $L(PATH_j)$ are the path lengths of $PATH_i$ and $PATH_j$, which can be expressed as

$$\begin{cases}L(PATH_i)=\sum_{p\to q\in PATH_i}w_{pq}\\ L(PATH_j)=\sum_{p\to q\in PATH_j}w_{pq}\end{cases} \quad (15)$$

Proof: If the wave propagates along $PATH_i$, then

$$\begin{aligned}T_i&=t_{fire}^{i}-t_{fire}^{Target}\\ &=(t_{fire}^{i}-t_{fire}^{R_i^P})+(t_{fire}^{R_i^P}-t_{fire}^{R_{R_i}^P})+\ldots\\ &=\sum_{p\to q\in PATH_i}-\frac{w_{pq}}{B}\ln(\alpha B)\\ &=-\frac{L(PATH_i)}{B}\ln(\alpha B)\end{aligned} \quad (16)$$

where $\alpha=u_{ij}/w_{ij}$, it is clear that α is a by constant Condition (III) . Similarly, if the wave propagates along $PATH_j$

$$T_j=-\frac{L(PATH_j)}{B}\ln(\alpha B) \quad (17)$$

Since Conditions (I) and (II) hold

$$-\ln(\alpha B)>0 \quad (18)$$

Thus:

(I) If $T_i\geq T_j$, then $L(PATH_i)\geq L(PATH_j)$;

(II) If $L(PATH_i)\geq L(PATH_j)$,then $T_i\geq T_j$.

This completes the proof of Theorem 2.

5. Simulation for PCNN Model in MALT system

The target is located in the range of $700\times 700(m)$, and the real position and measured location of the target are recorded. The simulation results are as Fig.6. The straight line represents the true position of the target, and the star fold line represents the measurement position. And the mean square deviation is shown in Fig.7..

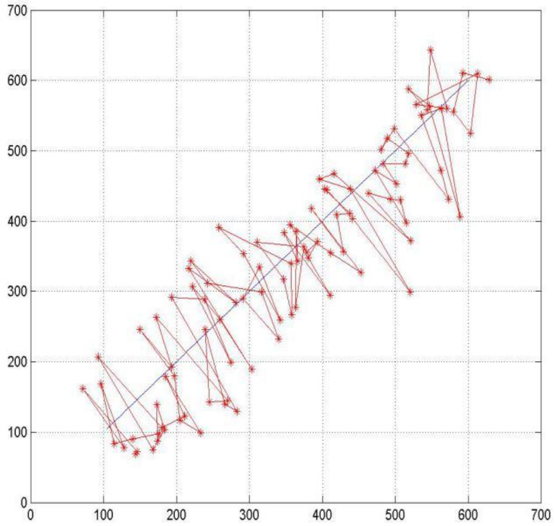

Fig.6 Comparison diagram of real and measurement position

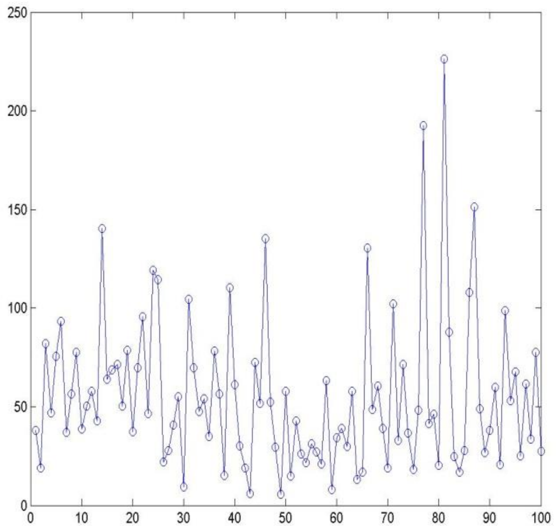

Fig.7 The mean square deviation of the target position

After locating the target by MLAT system, realizing the path planning of aircraft and vehicle in the scene. We use the theory mentioned above to simulate the graph 5.

Consider a real example as illustrated in Fig. 1, where S is the location of the start, E is the location of the target, and 11,12,13,21,22,23,24,31,32,33 are the locations of transfer station. In this example, which satisfied the conditions in Theorem 1.

Consider the dynamics of each neuron step by step.

1）At time 0, neuron S fires, thus $t^S_{fire}=0$

Then

$$\theta_{Si}(t)=\exp\left(w_{Si}\right),\quad i=11,12,13$$

$$\frac{dx_{Si}(t)}{dt}=x_{Si}(t),\quad i=11,12,13$$

else

$$\theta_{ij}(t)=\exp\left(w_{ij}\right)$$

$$\frac{dx_{ij}(t)}{dt}=0$$

2）At time $t=\ln\left(4\right)$,for $i=12$, we have

$Y_{12}(t)=1$

Thus, when the neuron E fires, stop.

Then the movement is

$$1\rightarrow R_1^P\rightarrow R_{R_1^P}^P\rightarrow\ldots$$

That is $S\rightarrow 12\rightarrow 21\rightarrow 33\rightarrow E$

The finding shortest path is shown in Fig 8-Fig 11.

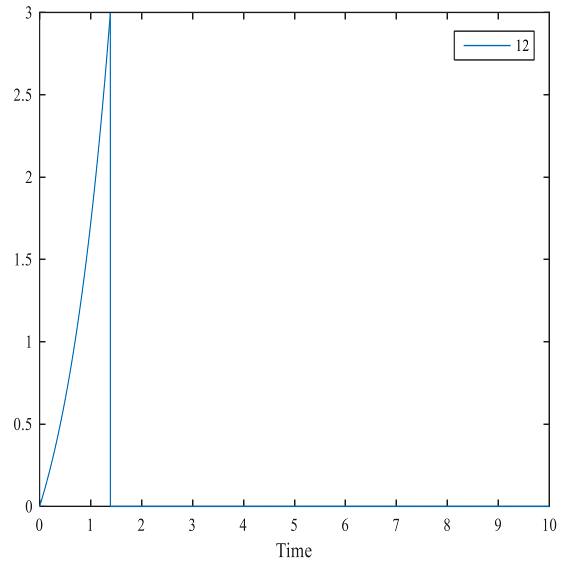

Fig.8 The Firing sequence and time of the neuron 12

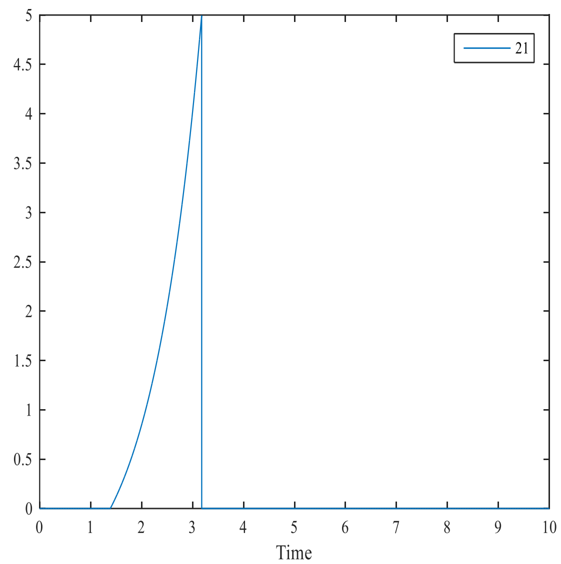

Fig.9 The Firing sequence and time of the neuron 21

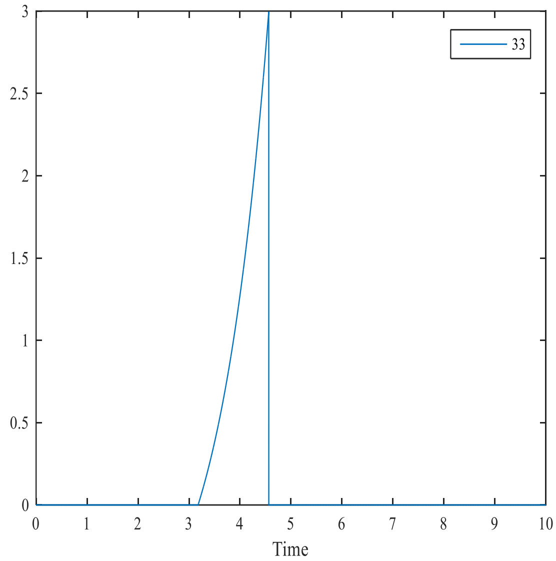

Fig.10 The Firing sequence and time of the neuron 33

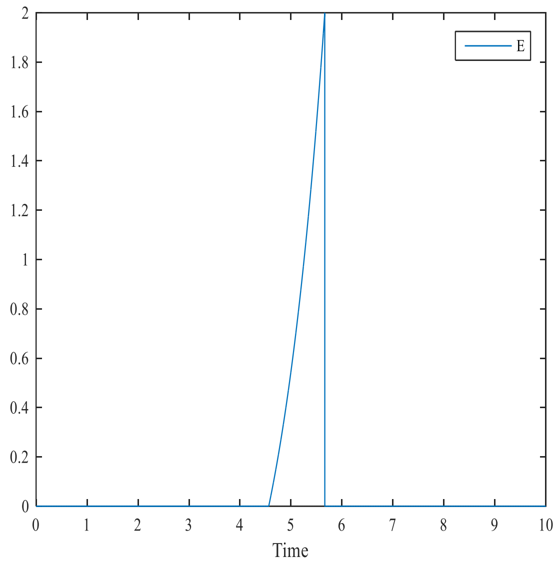

Fig.11 The Firing sequence and time of the neuron E

In this example, describe how the proposed model worked step by step. In the Fig.8-Fig.11, it illustrates the firing sequence and time of the neurons which are on the shortest path.

6. Conclusion

MLAT system is used to locate the target. The high-precision positioning method provides more reliable location information for aircraft and vehicle monitoring in the scene. Then these traffic tools are modeled by path planning, the article proposed that fast and accurate finding the shortest path is a simple and easy model, which not only maintains the important properties of the typical PCNN model. The complexity of the algorithm is only related to the shortest path length and the complexity of the map. It does not need any prior knowledge and does not need to optimize the cost function. In addition, there is no comparative calculation in the wave propagation of each neuron. The feasibility and correctness of the method are verified by simulation and theoretical analysis.

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Zhao Tongjuan is currently pursuing her PhD study at the School of Economics and Management, Yanshan University, Qinhuangdao, China. She obtained her BS degree from INNER MONGOLIA NORMAL University, China in 2001 and her MS degree from SCHOOL OF SCIENCE , Yanshan University, Qinhuangdao, China. 2005. Her main research interests are in the areas of queuing theory , supply chain.

Wang Jiuhe graduated her PhD study at the School of Economics and Management, Yanshan University, Qinhuangdao, China in 2007. He obtained his BS degree from Economics and Management, Yanshan University, Qinhuangdao, China in 1992 and his MS degree from Economics and Management, Yanshan University, Qinhuangdao, China 1995. His main research interests are in the areas of Logistics and supply chain management, organization management innovation strategic human resource management. He is a Doctoral supervisor in Yanshan University.