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Artificial Intelligence Based Mobile Tracking and Antenna Pointing in Satellite-Terrestrial Network

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ABSTRACT In recent years, mobile services have developed rapidly and traditional satellite-terrestrial networks have been unable to support them. We are faced with the problems of how to locate mobile terminals accurately and process the data we collected quickly to reduce communication pressure. In order to solve this problem, this paper studies a pointing and tracking method based on artificial intelligence for mobile stations and terminals in satellite-terrestrial network, to make sure that our mobile stations and terminals can access best antenna signal and suffer minimal communication interference from other stations or terminals. An AI-based self learning (ASL) network framework is designed to support filtering and correct original sampling data, mobile tracking of mobile stations and terminals, and unsupervised satellite selection and antenna adjustment scheme. Deep learning of historical information data of stations and terminals to achieve real-time pointing and tracking, and predict the distribution of stations and terminals at some time in the future. Finally, the ASL is compared with existing systems to measure their functionality and usability.

INDEX TERMS Satellite-terrestrial network, artificial intelligence, mobile tracking, deep learning, unsupervised self learning.

I. INTRODUCTION

With the rapid growth of mobile services supported by satellite-terrestrial network, both data transmission and data analysis require more and more resources and time consumption [1], [2]. So, it is becoming more and more difficult to provide high quality services in satellite-terrestrial networks [3], [4]. As the number of mobile stations and devices continues to increase, the quality of service of traditional satellite-terrestrial networks is likely to decline. Moreover, the mobile device's movement trajectory is very complicated, and the traditional satellite terrestrial network is difficult to quickly cope with the communication of multiple complex mobile devices. Therefore, AI-based data analysis and mobile pointing and tracking for stations and terminals are especially important.

Many researches have focus on analyzing various kinds of data in satellite-terrestrial network for better development of the related industry [5], [6]. However, these methods do not take into account the impact of big data. Current artificial intelligence technologies can be integrated with geo-spatial information science so that we can perform geospatial information collection, intelligent data analysis and geo-spatial data driven applications [7], [8]. Thus, artificial intelligence can be applied to the design and operation of satellite terrestrial networks. We divide this method into three steps: data analysis, data acquisition, and feedback adjustment. But how do we improve our mobile communication services' quality on satellite-terrestrial network? Unsupervised learning and reinforcement learning come in handy at this time.

During communicating among satellites, ground stations and terminals in satellite-terrestrial network, we need to precisely point and follow the mobile target [9]. This is because the relative movement between satellites, stations or terminals requires adjusting the pointing of satellite antenna on time to get the best signal reception requirement. As for the mobile services in satellite-terrestrial network, poor ground conditions will cause severe turbulence in the mobile carrier, and the antenna azimuth and elevation of the ground mobile station and terminal will change rapidly. In order to

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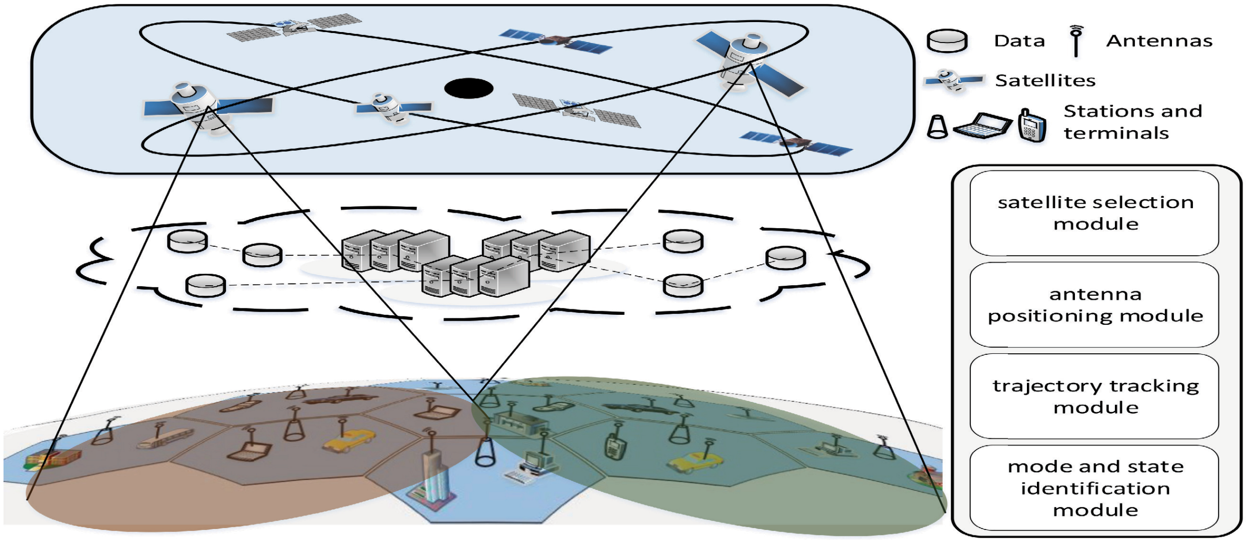

FIGURE 1. ASL network framework.

improve the communication performance between satellites and ground stations or terminals, we need to achieve pointing and tracking of the antenna on the stations and terminals, to ensure that our antenna beam will always point at the suitable satellite [10], [11]. The pointing and tracking in satellite-terrestrial network integrate many kind of technologies, for example, data acquisition and signal processing technology, satellite communication technology, sensor technology, edge-cloud computing, and so on [12]–[14].

This paper puts forwards an AI-based self learning framework of perception-interaction-control, assisted by artificial intelligence and considers the quality of mobile communication on satellite-terrestrial network, and it explores a new way to integrative collaboration and interaction with mobile targets. First, we need to consider multi-mode perception information, using various types of sensors to perceive information about moving targets. Then, mobile pointing and tracking model are established. In addition, we use unsupervised learning to allow satellite-terrestrial network to acquire data from different environments and train, optimize allocation of resource, and learn to schedule its tasks [15]. In the end, in order to improve the practicality of this program, we will establish an effective system platform and solution.

The rest of this paper will be arranged as follows: Section II introduces the ASL network framework of perception-interaction-control. The mobile pointing and tracking of stations and terminals are described in section III. Unsupervised satellite selection and antenna adjustment are given in section IV. Finally, section V concludes the paper.

II. ASL NETWORK FRAMEWORK

The ASL network framework is established as shown in Fig. 1 for data filtering and correction, pointing and tracking of mobile stations and terminals, and unsupervised satellite selection and how mobile stations and terminals adjust their antenna. The system structure mainly includes the antenna pointing module, mode and state identification module, trajectory following module, and the satellite selection module for the mobile stations and terminals. Various sensors are equipped on mobile stations and terminals, including whole-site sensing instrument, inclinometer, GPS, compass,gypo compass, receive signal level, inertial navigation unit and so on. According to their real-time and historical sensing data, we designed unsupervised learning and reinforcement learning to learn and build the data analysis model to find the rules we don't know yet. The inclinometer and gypo compass are mainly used to detect and adjust the antenna angle of the stations and terminals, then optimize the transmission quality of data and the rational allocation of resources by adjusting the antenna angle and selecting the most suitable satellite. GPS, inertial navigation unit, etc. are used to assist in the pointing and tracking of our mobile stations and terminals. Combined with the artificial intelligence method, the collected historical information from sensors can support self-learning [16], such as direction, angle and speed, which we can predict the future position of our mobile stations or terminals, then we can quickly adjust the antenna angle and re-selecting the associated satellite when they are changing their positions, which in order to enhance the communication quality of the network. The ASL network framework also adopts installs electronic compass and inclinometer on the satellites, by combining with embedded control unit and spectrum analyzer, the pointing of mobile stations and terminals can be implemented more accurately. In addition, in order to enable the mobile stations and terminals on the earth to obtain the maximum antenna signal and complete the data communication, we can use other algorithms such as Markov decision process or value iteration in reinforcement learning. This design can reduce the communication interference of satellite communication by the terrestrial network of adjacent stations and terminals within a certain range.

We should make sure the performance of pointing and tracking process, because it is very important to train the massive data. The ASL network framework leverages the cloud processing platform to facilitate data transfer. In other words, we can program in the cloud processing platform to achieve processing and analyzing massive data. We use the self-learning ability of artificial intelligence to feed back the results of data processing and analysis to the calculator and controller, which can achieve antenna angle adjustment for satellites, mobile stations and terminals, as well as choosing the best satellites for mobile stations and terminals.

III. MOBILE POINTING AND TRACKING OF STATIONS AND TERMINALS

In order to achieve the purpose of targeting and tracking, this paper designs the methods that can filter and correct the sensing data which from mobile stations and terminals. So that we can reduce the impact of uncertainty caused by interference and other factors in the communication between satellites and mobile stations on the perceived data, as well as terminal. In addition, in order to improve the recognition of the motion mode of the mobile terminal, we discussed the statistical-based learning method and the inference mechanism, and established the classification and recognition model, which can greatly improve the motion recognition of the mobile stations or terminals. Moreover, we use an effective perceptual decision-making reasoning mechanism to reduce the uncertainty of self-organization and data dependence in the calculation process.

When performing motion state recognition of mobile stations and terminals, it is impossible to record all motion processes. We only extract representative key frames. This paper uses the idea of local linear embedding to extract key frames so that local linear features can be preserved when mapping data to low-dimensional manifold spaces. Then we use the support vector machine (SVM) to classify and train the key frames, and associate the key frames with the basic motion coding set to achieve the motion state recognition.

After the motion state of the station or terminal is identified, the pointing is then achieved by the analysis of the remote sensing image (RS) acquired by the satellite. Before acquiring the RS, the satellite angle is required to be adjusted first, to ensure that our satellites can cover all areas of the ground. In addition, the mobile stations or terminals on the ground always communicate with the those satellites whose can cover them. The satellite antenna installed inclinometer and electronic compass to correctly control the angles of azimuth and elevation, as shown in Fig.2. They send the current azimuth angle and elevation angle of the satellite antenna to the embedded control unit in the form of digital quantity, and compare the value with the calculated value in embedded control unit from computer. If it is less or larger than the value that we calculated, the program controls the adjustment of pan-tilt, until the current value

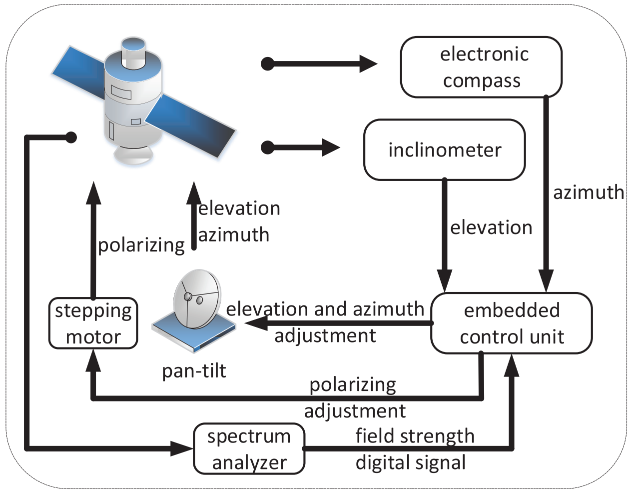

FIGURE 2. Adjustment of satellite antenna. Motion State Identification and Pointing.

and the calculated value are equal. After that, the embedded control unit controls the polarizing angle of the low noise block (LNB) through the stepping motor, and the feedback information of the LNBąŕs polarization angle is received by the spectrum analyzer. One side of the spectrum analyzer is connected to the signal line of the satellite antenna LNB while the other side is connected to the satellite receiver, and the digital signal of the field strength indicating circuit is inputted to the embedded control unit. The embedded control unit can determine if satellite signal field intensity become the strongest according to the display level, and then it can rotate the LNB of stepping motor to get the best signal.

After adjusting the satellite angle, RS from the ground can be collected as an important source of information. This paper determines the characteristics of the target and achieves the pointing based on the target features. In addition, we need to ensure that the target in the satellite terrestrial network needs to ensure the accuracy of the information and the integrity of the extraction in the RS. But now the RS target pointing are low accuracy and it will take a long time. So, a satellite RS target pointing method is proposed to detect the target edge shown in the satellite RS through evaluation index of edge detection based on canny operator [17]. Based on the result of edge detection, the target pointing method creates a transformation model, and achieves the target orientation by extracting the target feature and describing the match [18].

A. TRAJECTORY TRACKING AND BEHAVIORAL INTENTION COGNITION

Motion capture technology is developing very well today, we can easily get the mobile stations and terminals? motion data. Sensors such as GPS, compass, and monocular cameras can calculate three dimensional movement data. The mobile station or terminal motion data are the carrier of behavioral intentions, which contains plenty motion information. When tracking a target, in order to predict its trajectory, we can use artificial intelligence to analyze the acquired motion data, so that we can track the target more accurately and quickly. Therefore, this paper gives a behavior intention which can understand the method based on mobile station or terminal movement data. We can use artificial intelligence systems to analyze historical assessment data, summarize digital experience, and judge future trends. It can realize realizing the fast adjustment of mobile stations and terminal antennas, and select the satellites to increase the quailty of communication of the framework.

In order to predict task intention, the behaviour perception handle the early motion in the task to get this, logically infers the execution of the following task as well. In this process, various motions are causal, and we can simulate them with a probability network. This paper uses the probabilistic network-based reasoning method to reason the behavior of mobile stations or terminals. First, the recognition of an action attribute is determined by the action generated, and an expected outcome is calculated based on the outcome of the recognition. It then makes a probabilistic determination of the actions that may occur in the previous step, based on the probability of the expected result, to determine the remaining inverse probability performance for the entire process. Finally, based on the results of probabilistic reasoning, there is a path of travel that increases the probability of selecting the expected result. In this way, the direction and predictions of the mobile station or the terminal are monitored.

IV. SATELLITE SELECTION AND ANTENNA ADJUSTMENT

In satellite-terrestrial networks, the antenna azimuth and elevation of mobile stations and terminals will change with satellitesąŕ and their locations. In order to establish stable ground and satellite communication, rapid antenna pointing and tracking are necessary for selecting suitable satellite for mobile stations and terminals. To achieve this purpose, the antenna beam of the mobile station or terminal needs to point in the direction with the peaking signal.

A. ANTENNA POINTING AND TRACKING

In order to achieve the antenna pointing and tracking in satellite-terrestrial network, we take unsupervised learning to use sensory data of the satellite-terrestrial network as input to train those data. The transfer packet will contain many kinds of target data, such as speed of movement, location information, etc. are important. The importance of them can be quantified to use the target preference function $u(x) = \Sigma_{k=1}^{n}\omega_i \cdot u_i(x)$, where ω_i is the target weight and $\Sigma_{k=1}^{n}\omega_i = 1$, and $u_i(x)$ is the preference value. In order to obtain valuable information, we process and classify the input data through unsupervised learning.

The current environment is modified according to the modification rules, and then the simulated decision vector is obtained [19]. The decision-making index is extracted from the simulated decision vector, and is used to estimate whether a certain planning method combined with probing mode, pointing, and spectral segment satisfies the target threshold. If not, the above process is repeated and a new planning method is put forward, until the target threshold is met. Using the stress imaging simulation vector which based on path and parameters, the best combination of parameters and paths can be obtained by adopting the specific algorithm cyclic parameters and path planning. Moreover, according to the fuzzy statistical mathematics principle and the bayesian theory prior method [20], the prestige of the sensor participating in the decision is calculated based on the data generated from the sensor in real time, and the minimum range of comprehensive decision processing can be realized. Finally, parameter and path planning scheme is returned to the case library as the final decision vector in the best mode.

B. SATELLITE SELECTION AND ANTENNA ADJUSTMENT

In terms of pointing and tracking of mobile stations, terminals and satellites, while considering network throughput and energy efficiency, how to search for the direction of peaking signals between mobile stations or terminals and satellites is a challenging issue. The antenna azimuth, elevation and polarization of the mobile stations and terminals are regulated by the respective motors. When the station or terminal receives the strongest signal, the motor is set to have no motion, but when the station or terminal receives a weaker signal, the motor needs to be adjusted to find direction of azimuth, elevation and polarization. At the same time, we use machine learning methods to search for the direction of the peak signal.

This paper uses deep reinforcement learning to achieve peaking signal search. The reinforcement learning method is a kind of learning that maps from environmental state to action [21]. The goal is to get the maximum cumulative reward in the process of interacting with the environment, and trial-and-error methods are often used to find optimal behavioral strategies. The basic idea of reinforcement learning is to learn the optimal strategy for accomplishing the goal by maximizing the cumulative reward value that the agent obtained from the environment [22]. It can be further understood that if a certain behavioral strategy of the agent produces a satisfactory situation and a positive reward is obtained, the trend of generating and repeating the behavioral strategy will be strengthened. However, if a certain behavioral strategy of the agent receives a negative penalty from the environment, the trend of repeating the behavioral strategy will be weakened or prohibited. Therefore, the reinforcement learning method is more focused on learning strategies to solve problems [23]. This paper uses the markov decision process to model the fast search of peaking signals. The ground station or terminal acts as an agent, and its state space is the available bandwidth. The search space for the direction of the peaking signal is used as the action space.

As shown in Fig. 3, a mobile terminal T_k will change the selected satellite with stronger signal when it moves from position A to position B. Considering the following situation that the terminal arrives the position C, its antenna points to satellite S_i, there exist a satellite S_j with the strongest signal

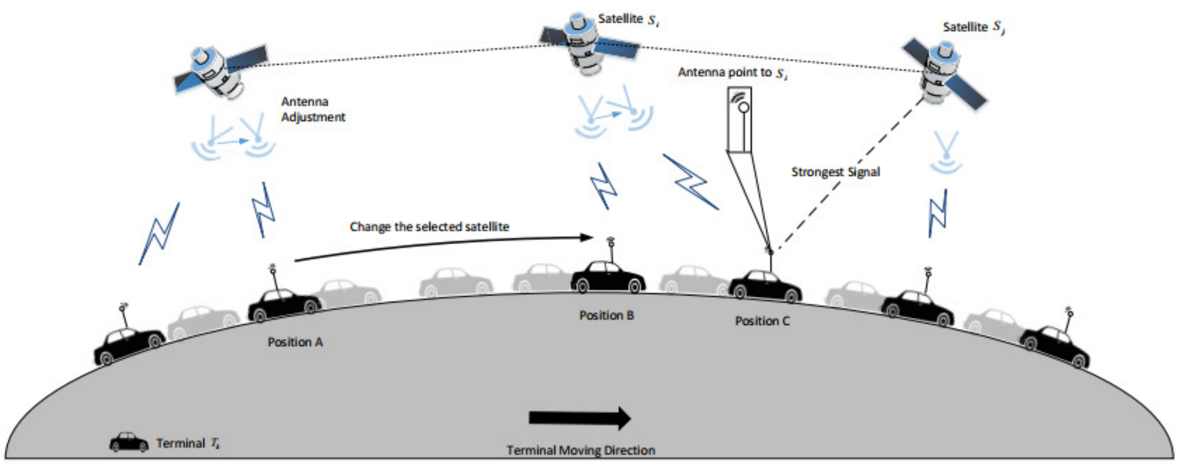

FIGURE 3. Satellite Selection.

TABLE 1. System comparison.

Systems	Artificial intelligence	Artificial adjustment	Trajectory prediction	Data sensing and analysis	Error processing	Energy reduction	Service area
ASL	yes	active	yes	measurement and deep learning	yes	yes	land and sea
PATT	no	active	no	measurement	yes	no	land and sea
ATS	no	passive	no	measurement	yes	no	land and sea
SBAS	no	active	no	measurement	no	no	sea

among candidate satellites, but pointing to S_j requires moving the antenna over a wide range, and pointing to satellite S_i can be docked with a small motor action. Thus, the benefits obtained by the mobile station or terminal are related to both the strength of the signal and the angle of rotation, and which is proportional to the strength of the signal and inversely proportional to the angle of rotation. To get the peaking signal, the high-dimensional sensing data that interacts with the satellite and the mobile station or terminal at each point of time is collected firstly. Each signal action (ie, motor motion) is then evaluated based on the expected return, and each action has only a limited next action in the motion space. Finally the motor reacts to this action and gets the next observation. By continuously cycling through the above process, the search for the peaking signal direction can be achieved.

C. COMPARISON AND ANALYSIS

In order to evaluate the proposed antenna pointing and tracking method, this paper compares the ASL network framework with some existing satellite antenna pointing and tracking methods. Dybdal and Soohoo designed a pointing and tracking technique (PATT) for narrow beamwidth satellite antennas for a limited number of array antennas when communicating with sparsely distributed domain users over a wide coverage area [24]. This technique utilizes an extension of the pseudo-random code and antenna tracking techniques to provide registration of the entire coverage area to the desired geographic location as well as acquisition and tracking by individual users. Moreover, a terrestrial beacon that transmits a pseudorandom code at a known location is used to register the entire coverage area. The tracking uses two beams in a single pulse to provide tracking information in one plane and subsequent measurements in orthogonal planes to determine angular position [25]. Aubert introduced the Astrium's Eurostar E3000 antenna tracking system (ATS) developed by the first fly on Astrium and KASAT. It significantly improves the antenna pointing accuracy and presents the efficiency and robustness of the antenna tracking system, which shows the ability to eliminate large transient errors from the stations maneuver or eclipse transition [26]. Gan and Yu put forward a space based augmentation system (SBAS) combined with precision point positioning for accurate pointing of ground terminals [27]. As shown in TABLE I, by adopting AI-based data analysis, the ASL framework can feedback data analysis result quickly and achieve accurate trajectory prediction, thus realize more efficient pointing and tracking to support large-scale mobile services in satellite-terrestrial network.

V. CONCLUSION

In this paper, the pointing and tracking for ground mobile stations and terminals in satellite communication system is realized by using artificial intelligence. The ASL network framework is proposed for pointing and tracking, and supporting unsupervised satellite selection and antenna adjustment. Then antenna adjustment is achieved based on the result of pointing and tracking, and the location prediction of the mobile stations and terminals in our future. Our satellite selection and antenna adjustment for peaking signal is realized by unsupervised learning. Finally, the proposed ASL network framework is compared with some existing systems to measure their functionality and usability of pointing and tracking.

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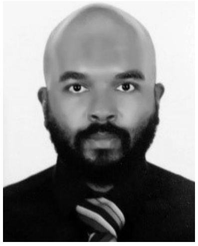

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