Acta Technica 62 No. 1B/2017, 325–336

Chaotic time series prediction based on the fusion of multi-source collaborative data feature constraints

BaoYan Zhang[1]

Abstract. With the continuous development of multi-source collaborative data network technology, multi-source collaborative data has been widely applied and become an important infrastructure in the field of information technology. However, the intelligent prediction based on the fusion of multi-source collaborative feature constraints often fails to obtain the accurate predictive relevant real-time information as the chaotic time series perceptual information demand of intelligent applications normally cannot be translated into simple query requests and multi-source sensor underlying query interfaces. In view of this problem, a multi-source collaborative data network information resource description, reasoning and application model based on the fusion of multi-source collaborative data feature constraints is proposed in this paper, which combines, and on the basis of the chaotic time series prediction support as the application foundation, the chaotic time series prediction technology based on the fusion of the multi-source collaborative data feature constraints is studied. Experiments prove that, the improved model can realize the accurate positioning of the specific multi-source sensor in the multi-source collaborative data network and obtain the real-time sequence prediction mechanism of the corresponding perceptual information.

Key words. Multi-source collaborative data, feature constraints; prediction, multi-source collaborative data network; chaotic time series.

1. Introduction

With the rapid development of artificial intelligence, the chaotic time series has been widely applied in the fields of intelligent transportation [1], military application [2], emergency handling [3], disaster relief [4] and other aspects. Chaotic time series often needs to obtain a lot of real-time information about the physical world in the course of the completion of the prediction tasks. For example, in the disaster rescue, when rescuing the people in the disaster area, it is required knowing the location of the wounded person, the surrounding environment, injury situation and so on, so that rapid and targeted rescue can be carried out. The emerging multi-

[1]School of Information Technology and Engineering , Jinzhong University, Jinzhong, Shangxi, 030619, China

source collaborative data network technology has provided a brand new perceptual information service mechanism with wide coverage, strong real-time performance and other features, and this information service mechanism is on the basis of the multi-source sensor network system with mutual communication and interoperability in the multi-source collaborative data network, to provide chaotic time series with extensive and comprehensive real-time information, so as to significantly improve the efficiency of the chaotic time series to accomplish the prediction task.

The disunity of multi-source data collaboration and heterogeneity of sensor information is a major bottleneck in the application of the autonomous planning and prediction support of chaotic time series in the multi-source collaborative data network [5–7]. It is a hot research topic in recent years on how to describe the multi-source sensor effectively and make use of the description information of the multi-source sensor in the acquisition and application of the perceptual information. Although the aforementioned research methods can achieve effective semantic representation of the multi-source sensors, they are not suitable for the direct application to the multi-source collaborative data network.

Firstly, the multi-source collaborative data network is a service network based on the fusion of the sensing resources [8–10]. Therefore, the semantic modeling for the multi-source collaborative data network must be service-oriented semantic modeling, and not just the semantic modeling for the multi-source sensor;

Further, in consideration of the availability of the sensor resources and the close correlation with the temporal and spatial features, in the semantic modeling, it is necessary to conduct unified modeling for the temporal and spatial features and the effectiveness of services [11–12].

On this basis, in this paper, a semantic modeling approach for the multi-source collaborative data network service resources and their temporal and spatial features. In the modeling approach: We first encapsulate the perceptual resources in the multi-source collaborative data network through the restful service to generate the corresponding multi-source collaborative data network resource service;

Furthermore, through constructing a semantic model for the restful services the semantic model, the semantic description of the multi-source collaborative data network service resources is realized. Finally, we introduce the temporal and spatial description method in the semantic model, and achieve the effective semantic modeling for the temporal and spatial features of the multi-source collaborative data network resource service.

In this paper, different from the former fusion based multi-source data collaborative feature constraint work, the multi-source collaborative data feature constraint prediction task planning method in view of the multi-source collaborative data feature constraints is put forward. The method can make full use of the semantic description meta-information in view of the multi-source collaborative data network resources, and realize the dynamic mapping from high-level semantic description information requirement to the underlying multi-source sensor resources by integrating the planning reasoning of the dynamic description logic. Based on this method, the chaotic time series prediction model can effectively utilize various existing multi-source collaborative data networks to realize the effective prediction task assignment, the real-time prediction task execution monitoring for various emergency prediction tasks in the physical world, and dynamic prediction task adjustment and prediction task re-planning, etc.

The complex prediction task here refers to the prediction task which needs to be completed by several agents collaboratively and collaboratively. Based on the team-oriented plan (hereinafter referred to as multi-source data collaborative feature constraints) [6], this paper constructs a new method for the prediction of the features of complex tasks. The reason of the fusion based multi-source data collaborative feature constraints to construct the multi-source data collaborative feature constraints is that: the multi-source data collaborative feature constraints can provide a framework to construct the prediction task feature constraint plan according to the behavioral capacity of each individual in the team. With the integration of this framework, effective breakdown of complex prediction tasks can be realized.

2. Chaotic time series prediction model based on the fusion of multi-source collaborative data feature constraints

2.1. Chaotic time series prediction mechanism

When an abstract complex prediction task is accomplished in the chaotic time series, it requires a lot of real-time information in the physical world as the prediction basis. However, the multi-source collaborative data network can be regarded as a database with the capability to provide massive information about the physical world. Therefore, we propose a chaotic time series prediction support system based on the fusion of the multi-source collaborative feature constraints (hereinafter referred to as CTSPSS for short). CTSPSS obtains the prediction task from the prediction task interface and passes it to the chaotic time series; the chaotic time series constrains the abstract complex task features to be completed as a series of sub-prediction tasks with lower coupling degree according to the prediction task knowledge in the knowledge base; and then, each sub prediction task is assigned to the specific agent.

The agent needs to perceive the real-time state of the physical world when it accomplishes the task, and it can make reasonable prediction on the basis. However, as the agent system usually describes the environment states that need to be perceived in the high-level semantic form (such as description logic), while for the heterogeneous multi-source collaborative data network entities (such as gateways and sensing nodes) in the multi-source collaborative data network, the perceptual information can only be exported through the specific query oriented method, therefore, CTSPSS can construct a multi-source collaborative data feature constraints based on the semantic model of the multi-source collaborative data network resources. The multi-source collaborative data feature constraints realizes unified description on the individual attributes and access interfaces of the multi-source collaborative data network resources through the resource description method of the fusion ontology, so that the chaotic time series can obtain the corresponding multi-source collaborative data network resources by analyzing the semantic description. The chaotic time series can constrain the complex prediction task features into a series of simple prediction tasks, and obtain the chaotic time series perceptual information needed to accomplish the simple prediction task in the multi-source collaborative data network.

To sum up, whether it is possible to obtain the required information resources to predict the execution of the task from the multi-source collaborative data network determines whether the prediction task can be successfully executed. Therefore, when the prediction task feature constraints are conducted, the chaotic time series needs to determine whether the resources in the multi-source collaborative data network can meet the information requirements of the prediction task execution. In the following section, we will discuss in details how the chaotic time series can perform the prediction task feature constraints according to the available information resources in the multi-source collaborative data network. First of all, it is required making formal specification on the problem of chaotic time prediction task feature constraint prediction for the multi-source collaborative data network.

Definition 1. A prediction task T is a two-tuples with the form of $T = \langle Init, Goal\rangle$.

$Init$ and $Goal$ are both state description sets, $Init$ and $Goal$ are composed of a set of description logic formula. In which, $Init$ represents the system state before the execution of the task; and $Goal$ is the expected system state after the task is executed, that is, the target state.

Definition 2. The breakdown scheme of a prediction task T is a four-tuples with the form of $Schema\,(T) = \langle TaskSet, State, Action, QuerySet\rangle$.

Quantity $TaskSet = \{T_1, T_1, \dots, T_n\}$ is the set of the sub-prediction task broken down by the chaotic time series according to the knowledge base, T_k is the kth sub prediction task, $State = \{state_1, state_2, \dots state_n\}$ is the environmental information needed to accomplish the sub prediction task, where $state_k$ is the environment information needed to accomplish the abstract complex prediction task T_k, $Action = \{A_1, A_2, \dots A_n\}$ is the behavioral prediction needed for the agent to accomplish the prediction task, in which, $A_k = Decision\,(T_k, state_k)$ is the action prediction taken by the agent to accomplish the sub prediction task T_k, $QSet_k = \{Q_1, Q_2, \dots, Q_M\}$, $QSet_k \in QuerySet$ is the set of the environment information required to accomplish the sub prediction task T_k. Obviously, $QSet_k$ is determined by $state_k$.

For example, assuming that the chaotic time series receives an abstract complex prediction task “Fire fighting for building B”, through breakdown, a number of sub-prediction tasks can be obtained, in which, the sub-prediction task T_i is "The fire engine arrives at the scene of the fire". In order to accomplish the sub-prediction task, the required environment state perception is state= "Traffic state from the fire site to the fire center". Although the multi-source collaborative data feature constraint is constructed, and the semantic information fusion query can be realized, but as the query granularity is relatively large, the multi-source collaborative data network cannot directly understand and complete this type of environmental state query, therefore, it is necessary to further break down the abstract state query, and ultimately generate the semantic query operation that can be directly understood and executed by the machine, $QuerySet = \{Q_1 =$ "Beijing No. 1 Road traffic pressure multi-source sensor state", $Q_2 =$ "Beijing No. 2 Road traffic pressure multi-source sensor state", Q_3 = "Beijing No. 1 Road traffic lights state", Q_4 = "Beijing No. 2 Road traffic lights state", ... }. Through these specific query statements, the chaotic time series can obtain the necessary environmental information from the multi-source collaborative data network.

2.2. Chaotic time series prediction based on the fusion of multi-source data collaborative feature constraints

As mentioned earlier, action prediction relies on the real-time sensing of the environment information state. However, state is usually a relatively abstract state of the environment, making it difficult for the machine to directly map the state queries to the directly executable multi-source collaborative data network atomic query statements. Therefore, CTSPSS requires the query breakdown process that maps the state abstract query to a specific atomic query set QuerySet. According to QuerySet, CTSPSS can determine whether the multi-source collaborative data network can provide the necessary information support for the action execution.

The process of breaking down the state query is a semantic breakdown process with decreasing abstraction degree by layer, and the semantic breakdown by layer can be achieved through the prediction task feature constraint knowledge in the multi-source data collaborative feature constraint knowledge base. However, the multi-source data collaborative feature constraint knowledge base is usually oriented to a specific prediction task, while state usually represents a more general physical world state. Therefore, it is very difficult to identify a multi-source data collaborative feature constraint breakdown Map to correspond to the state. Therefore, we try to construct a state query breakdown method based on the fusion ontology.

It can be known from Algorithm 1 that the information that needs to be queried from the multi-source collaborative data network is a subset of the action execution preconditions set, and the action execution prerequisite represented by the dynamic description logic consists of two forms: the conceptual assertion formula with the form of $C(x)$ and the relation assertion formula with the shape of R. Their respective implication is that: If individual x is an instance of C, the precondition holds; if there is R relationship between individual$x$ and individual y, this prerequisite holds. The prerequisites of both types can be regarded as the state verification of the individual in the physical world, for example, HighTemperature represents the verification whether the temperature of room r is too high, and InSameRoom represents the verification whether x and y are in the same room, etc.

To simplify the discussion, we assume that the multi-source collaborative data network only provides the perceptual information on the attributes of various physical objects in the physical world, such as the physical object location, running speed, running direction and so on. At the same time, such attribute information can be obtained from the multi-source sensor associated with the physical object. Therefore, the problem of the state verification for a physical object can be converted to the acquisition of the perceptual information about the multi-source sensor associated with the physical object. Furthermore, since the physical object-related chaotic time series implies that the information acquisition of multi-source sensors requires temporal-spatial constraints, the state verification of the physical object can be mapped to the acquisition behavior of certain types of perceptual information in certain time period and spatial domain. Based on the aforementioned analysis, we can transform the verification of the physical object state of the action execution prerequisite to the breakdown query of the perceptual information with the temporal and spatial constraints, and finally form a series of query requests related to the multi-source sensor in the multi-source collaborative data network.

Through the ontology, we can represent a variety of perceptual information required for the validation of a certain physical object state, such as the state validation on whether a room is on fire can be expressed as the concept definition of and regarding to RoomOnFire:

RoomOnFire $\equiv$ Room $\sqcap$ hasSensingDevice.($\exists$ hasLocation.(InRoom $\sqcup$ NearRoom) $\sqcap$ observes.(Pmperty$\sqcap$Smoke)$\sqcup$observes.(Pmperty$\sqcap$HighTemeration))).

The specific meaning of this concept definition is that: If the multi-source sensor that is located in a room near the room detects smoke or temperature increase, the room has an outbreak of fire.

According to this definition, it is possible to determine the state of RoomOnFire (No.116) by obtaining the chaos time series perceptual information about the smoke and temperature of the multi-source sensor in the room No. 116 or in the vicinity of the room.

It can be noted that the concept definition that describes the physical entity state only describes the logical relationship of the perceptual information related to the state concept itself, while lacks the temporal and spatial constraints. Therefore, in the actual query breakdown, it is necessary to combine the concept definition with the temporal and spatial concept to form the query with the temporal and spatial constraints. For example, the temporal and spatial constraints as the following:

RoomFireState $\equiv$ RoomOnFire $\sqcap$ hasTime.("2012-l-8") $\sqcap$ hasLocation.("168Express Hotel").

The concept of the temporal and spatial constraints corresponds to a query on whether there was the information on an outbreak of fire in a room at 168 Express Hotel on July 8, 2012. After the temporal and spatial constraint is added, the status validation *RoomFireState*(No.116) on the physical object "No.116" is conducted. When "No.116" is located at the hotel "168 Express Hotel", the time is "2012–7–8", and the state of RoomFireState (No.116) is true, *RoomFireState*(No.116) returns the true value.

It can be seen from the aforementioned analysis that, the query breakdown for the conceptual assertions is the basis of the whole physical object state verification. Therefore, we need to design a query breakdown method for the conceptual assertions. The basic idea of this query breakdown method is as the following:

For a conceptual assertion $C(x)$, first of all, search for the concept definition of C in the ontology, if it cannot be found, it will return that system cannot verify $C(x)$; If the corresponding concept definition is found, the system will breakdown the concept definition according to the nested form of the concept into a tree structure (as shown in Fig. 1), and try to gradually match with the multi-source collaborative data feature constraints from the leaf nodes, to explore whether there is instance object in the multi-source collaborative data network information database that can satisfy the semantics of the node.

Then, the sibling nodes of the breakdown tree are merged to generate a new concept node, and the new concept node is matched with the multi-source collaborative data feature constraint and so on until the root node of the tree is matched. If the root node of the tree is matched, and there is object in the multi-source collaborative data network that belongs to the concept of the root node, the object is further filtered by the temporal and spatial constraint.

Finally, if there is an instance of the concept corresponding to the root node that satisfies the temporal and spatial constraints, query breakdown can be implemented on the system returns.

In order to improve the breakdown efficiency of the conceptual assertions, we define certain specification on the form of concept definition. The specification states that: The root node of the breakdown tree corresponding to the concept definition must contain a child node with the form of $\exists$ *hasSensingDevice*.(), and the child node has intersection relations with other sub nodes. That is, the concept definition must be the intersection of the concept and the sets with certain multi-source sensors.

Furthermore, through the analysis on the sub-tree with $\exists$ *hasSensingDevice*.() as the root node, it is possible to obtain the corresponding multi-source sensor set which can verify the state of the object, and then through the temporal and spatial constraint relationship, the corresponding perceptual query set can be determined.

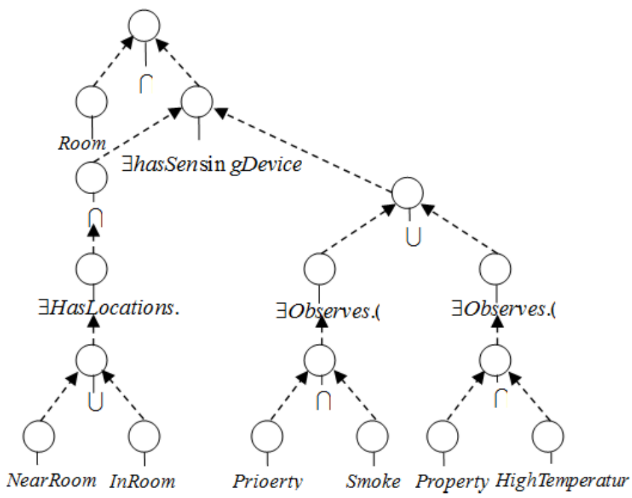

Fig. 1. Concept hierarchical tree example

3. Experimental analysis

In order to validate the proposed semantic prediction support technical scheme of the multi-source collaborative data network based on the fusion of the chaotic time series proposed in this paper, we analyze the availability and advancement of this design by the application of an implemented insurance accident handling command support time series prediction system as an example. The implemented overall framework of the system is shown in Fig. 2.

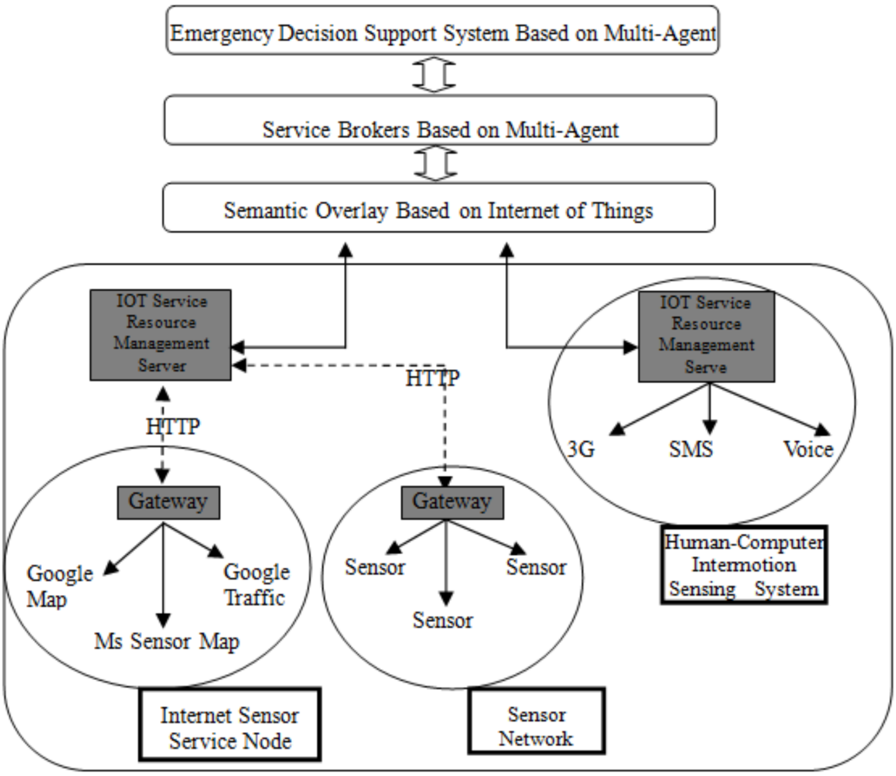

Fig. 2. Frame diagram of time series prediction system for command support in insurance accident handling

In this system, we define the multi-source collaborative data network sensor node can be connected through the 6LowPAN and other protocols to the gateway. The gateway registers the service information of the multi-source sensor node with which it is connected to the IOT service resource management server. This process can be achieved through manual construction or automatic discovery and other methods. Due to the lack of the corresponding physical multi-source sensor support, we adopt Google Map and Microsoft Sensor Map and other virtual multi-source sensor services for the case verification. At the same time, the program takes the smart phone as a special type of human-computer interaction multi-source sensor, and the smart phone can obtain user information and status through 3G, voice, text messages and other methods, and can also give commands to the designated executor. In respect of the physical multi-source collaborative data, we have defined the resource management server to generate its semantic meta-information about the IOT registration service. There are multiple IOT service resource management servers in the system; therefore, the service resources and its corresponding semantic meta-information are distributed. Distributed semantic meta-information stored in each resource management server has formed the multi-source collaborative data feature constraints. The service agent system composed of the chaotic time can achieve the multi-source collaborative data network resource discovery and service agent, etc. through the distributed semantic reasoning. In this system, all the breakdown, matching, resource positioning on the query is completed by the service agent system. And the chaotic time emergency accident handling system is above the service agent system, which obtains the IOT real-time information through the service proxy system, and implements the corresponding prediction task feature constraints and execution for the insurance accident emergency accidents.

For the specific traffic accidents, the system has formed the specific implementation scheme through the prediction task feature constraints as shown in Figure 3. By the query breakdown of the fusion based multi-source collaborative data feature constraints, the variety of information requirements in the prediction task is finally transferred into a series of sensor information query and management information query. According to the finally obtained prediction task query system and the underlying multi-source collaborative data, information is acquired and returned to the user for the predictive support.

The implementation process of the insurance accident handling command support time series prediction system is shown in Figure 8, and its basic process is as the following:

When a traffic accident occurs, the system makes the accident notification, chaotic time series breaks down the prediction task, first conducts inspection on the policy, and sends the detailed information of the accepted policy to the forecaster.

Call out all underwriting vehicles information in the vicinity where the accident occurs. The system will automatically generate the location where the accident occurs on the map on the basis of the accident report, and at the same time, according to the vehicle status, mark the current location of the underwritten vehicle and its free status on the map, and automatically prioritize all the underwriting vehicles executing the prediction task for the forecaster to select the underwriting vehicle to perform the prediction task;

According to the selected underwriting vehicles, the multi-agent system provides the current road condition and multiple routes planning through the GoogleMap road condition. The forecaster selects the route of the prediction task execution according to the road condition.

When the route selection is successful, the system automatically generates the prediction task execution information, and sends text messages to the staff on board the vehicle through the system, to inform them the execution of the prediction task;

The chaotic time series obtains the information of the underwriting vehicle that executes the prediction task through the underlying multi-source collaborative data in real time to perform real-time surveillance on the underwriting vehicle. If the underwriting vehicle deviates from its prediction task execution route, the abnormal alarm feedback is provided to the forecaster, to help the forecaster track the latest state in real time and ensure that the prediction task is completed in a reasonable, fast and error-free manner, so as to avoid insurance fraud and other commercial crime incidents.

In the system implementation effect, we compare the efficiency of the accident treatment method of this system with the traditional accident telephone treatment method, including two aspects: the customer service of the insurance company headquarter reports the accident handling and the scheduling of the underwriting vehicle to the customer by phone. In the data analysis, we have intercepted the holiday peak travel period, that is, the period of time when the traffic accidents and congestion are most prone to occur, and the insurance company makes analysis on the ordinary accident handling records.

Table 1 shows the comparison data of the customer service handling time after the customer accident claim, as can be seen from the statistical results that: the support time series prediction system based on the fusion of the chaotic time can intelligently call out the customer insurance records, underwriting vehicle information and other materials quickly, to help customer service greatly shorten the accident service handling and service waiting time, and largely enhance the user experience effect.

Table 1. Test results of insulated resistance value (kΩ)

	Average customer service handling time per small accident (minutes)	Average customer service quantity per hours (number)	Average customer waiting time (minutes)	Average waiting queue (persons)
Traditional telephone accident treatment method	15	5	10	4
Time series prediction system for command support in insurance accident handling	5	10	Almost do not wait	0

On the other hand, in Table 2 we have provided the statistical comparison of the efficiency of the underwriting vehicles on the handling of the ordinary accident. It can be seen from the statistical results that: the system can provide intelligent prompts to the fastest way to arrive at the scene in the terminal of the underwriting vehicle driver through the multi-source sensor analysis on the traffic state, which has greatly reduced the time for the underwriting vehicle to reach the scene of the accident, lowered the consumption of fuel caused by the traffic congestion in the road, and enhanced the utilization efficiency of the underwriting vehicle. For example, the accident handling efficiency of the underwriting vehicle is increased by 28.8 %, while at the same time, the vehicle fuel consumption is reduced by 15.7 %.

Table 2. Efficiency comparison of the selection of underwriting vehicles on the accident handling route

	Average time of arrival of an accident (minute)	Efficiency enhancement	Reduction in monthly fuel consumption of underwriting vehicle
Driving based on the experience of driver	45	-	-
Driving based on the recommended route by the chaotic time prediction support system	32	28.8 %	15.7 %

4. Conclusion

The dynamic information service support of multi-source collaborative data network is the basis of the realization of the complex prediction task automation of the chaotic time series based on the fusion of the multi-source collaborative feature constraints. In this paper, the multi-source collaborative data feature constraint model of the multi-source collaborative data network is studied, and the breakdown method for the abstract complex prediction task based on the multi-source collaborative data feature constraints fusion and multi-source data collaborative feature constraints. Furthermore, the breakdown of the abstract environment state queries for the sub-prediction tasks is realized by the application of the multi-source data collaborative feature constraints and ontology knowledge base in this paper, and finally the information queries can be obtained directly from the multi-source sensors in the multi-source collaborative data network. Through the breakdown of the abstract prediction task twice, the system model proposed in this paper has successfully identified the corresponding multi-source sensor in the multi-source collaborative data network to provide the necessary sequence prediction for the chaotic time series.

References

[1] W. Y. Mu, R. Li, Z. Z. Yin, Q. Wang, B. Y. Zhang: *Fusion prediction of mine multi-sensor chaotic time series data.* Journal of Computer Applications *32* (2012), No. 6, 1769–1773.

[2] X. Cui, M. Jiang: *Chaotic time series prediction based on binary particle swarm optimization.* AASRI Procedia *1* (2012), 377–383.

[3] Y. Dang, X. Lv: *A chaotic time series crop forecasting model based on Bayesian semi-supervised SVR algorithm.* Journal of Computational Information Systems (2014), No. 10, 4179–4186.

[4] M. Assaad, R. Boné, H. Cardot: *A new boosting algorithm for improved time-series forecasting with recurrent neural networks.* Information Fusion *9* (2008), No. 1, 41–55.

[5] C. Bormann, A. P. Castellani, Z. Shelby: *CoAP: An application protocol for billions of tiny internet nodes.* IEEE Internet Computing *16* (2012), No. 2, 62–67.

[6] F. Zambonelli, A. Omicini: *Challenges and research directions in agent-oriented software engineering.* Autonomous Agents and Multi-Agent Systems *9* (2004), No. 3, 253–283.

[7] M. Compton, P. Barnaghi, L. Bermudez, R. García-Castro, O. Corcho, S. Cox, J. Graybeal, M. Hauswirth, C. Henson, A. Herzog, V. Huang: *The SSN ontology of the W3C semantic sensor network incubator group.* Web Semantics: Science, Services and Agents on the World Wide Web *17* (2012), 25–32.

[8] L. Chang, Z. Shi, T. Gu, L. Zhao: *A family of dynamic description logics for representing and reasoning about actions.* Journal of Automated Reasoning *49* (2012), No. 1, 1–52.

[9] W. Wang, S. De, G. L. Cassar, K. Moessner: *Knowledge representation in the internet of things: Semantic modelling and its applications.* Automatika–Journal for Control, Measurement, Electronics, Computing and Communications *54* (2013), No. 4, 388–400.

[10] I. F. Su, Y. C. Chung, C. Lee, Y. Y. Lin: *Efficient skyline query processing in wireless sensor networks.* Journal of Parallel and Distributed Computing *70*, (2010), No. 6, 680–698.

[11] K. P. Ferentinos, T. A. Tsiligiridis, K. G. Arvanitis: *Energy optimization of wireless sensor networks for environmental measurements.* Proc. IEEE International Conference on Computational Intelligence for Measurement Systems and Applications (CIMSA), 20–22 July 2005, Messian, Italy, IEEE Conference Publications (2005), 250–255.

[12] H. Gholizade-Narm, S. Chafi, M. Reza: *Using repetitive fuzzy method for chaotic time series prediction.* Journal of Intelligent & Fuzzy Systems *28* (2015), No. 4, 1937 to 1946.

Received June 29, 2017