데이터 스트림의 다중-간격 예측을 위한 통합된 계층형 시간적 메모리 네트워크
(An Integrated Hierarchical Temporal Memory Network for Multi-interval Prediction of Data Streams)

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요 약 데이터 스트림을 위한 효율적인 예측 방법을 개발하기 위하여 많은 연구들이 진행 되어왔다. 하지만, 이들 방법들은 대부분 고정된 시간 구간에 대한 하나의 예측 결과만을 제공하고 있기 때문에 많은 경우에 다양한 시간 간격을 기초로 얻어진 예측 결과들이 다를 수 있다. 따라서 다중-간격 예측(Multi-Interval Prediction; MIP)을 위한 새로운 방법의 개발이 요구된다. 본 논문은 계층형 시간적 메모리(HTM) 기술을 이용하여 데이터 스트림을 다중-간격 기반으로 예측할 수 있는 새로운 방안을 제시한다. 우리는 원래의 HTM 네트워크에 새로운 노드 형태인 Zeta1LastNode를 도입하여 통합된 계층형 시간적 메모리(Integrated Hierarchical Temporal Memory; IHTM) 네트워크를 제안한다. 특히, 이 IHTM 네트워크의 계층적인 통합 특성을 이용하여, 데이터 스트림에 대한 다중-간격 예측이 효과적으로 이루어질 수 있도록 하였다. 성능 분석을 통해 IHTM이 다중-간격 예측을 함에 있어서 예측 간격이 늘어날수록 원래의 HTM에 비하여 메모리와 계산 시간의 소비를 획기적으로 줄일 수 있다는 것을 보였다.

키워드 : HTM, IHTM, 다중-간격 예측(MIP), 데이터 스트림

Abstract There is a large body of ongoing research to develop efficient prediction methods for data streams. These methods provide single prediction with a fixed time interval. It is necessary to develop a method for multi-interval prediction (MIP) because different prediction results may be obtained based on different intervals in many cases. In this paper, we propose a solution for MIP based on the Hierarchical Temporal Memory (HTM) model. In order to solve the problem of MIP with HTM, we present an Integrated Hierarchical Temporal Memory (IHTM) network by introducing a new node type Zeta1LastNode to the original HTM network. Using the hierarchical characteristic of the IHTM network, different levels in the network learn and model the features of a data stream with different intervals and generate prediction results for different intervals. Performance evaluation shows that the IHTM is efficient in the memory and time consumption compared with the original HTM network in MIP.

Key words : Integrated hierarchical temporal memory (IHTM), multi-interval prediction (MIP), data streams

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1. Introduction

A data stream is a sequence of attribute value vectors. It arrives in a temporal sequence and may change over time. The prediction for a data stream is to decide the changing trend based on its past behavior. There are a number of attempts to develop efficient prediction methods for data streams [1-3]. Although traditional prediction methods work well, they provide a single prediction based on a fixed time interval. Many applications require multiple prediction results based on different time intervals for satisfying diverse requirements. Hence, we propose multi-interval prediction (MIP). The MIP is able to provide multiple prediction results simultaneously by choosing different intervals.

We use the Hierarchical Temporal Memory (HTM) model to solve the MIP problem for data streams. The HTM is known to be suitable for modeling and learning the spatial and temporal relationships between features of the real world [4,5]. Up to now, the HTM model has been applied to the prediction of data streams such as predicting the temperature and the trend of stock prices [6,7], but it is restricted to single fixed interval prediction. In order to solve the problem of MIP with HTM, we propose an Integrated Hierarchical Temporal Memory (IHTM) network constructed by introducing a new node type Zeta1LastNode to the original HTM network. Using the hierarchical characteristic of the network, we let different levels of the network learn and model the data streams with different intervals. After training, different levels of the network can generate prediction results for different intervals simultaneously.

This paper is organized in 6 chapters. In chapter 2, we define the MIP problem of data streams with HTM. We present the new node type for the HTM network to support MIP in chapter 3. The structure and operation of the IHTM network with the new node type is described in chapter 4. In chapter 5, we show the performance evaluation. Finally, we conclude the paper in chapter 6.

2. MIP of Data Streams with HTM

In this chapter, we give a brief introduction to the basic concepts in the MIP of data streams and introduce the problem of MIP with HTM.

2.1 Multi-interval Prediction

A data stream can be regarded as a sequence of attribute value vectors $s(t)$ [1]. The vector items based on different time granularity form a continuous flow of data like a stream. It maps each time point to a numeric value. Each data stream has an associated time interval $s(t)$: $t \in [t_s, t_e]$, where t_s is the starting time and t_e is the ending time. The $[t_{-12}, t_0]$ represents the sequence of vectors starting from t_{-12} and ending at t_0.

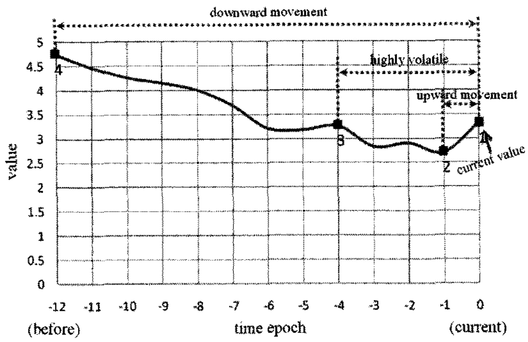

Fig. 1 Different prediction results with different intervals

Prediction for a data stream is to decide the trend of the changing movement. Traditional prediction methods are based on the length of the time interval of historical data, where the long term prediction requires longer intervals and short term prediction requires shorter intervals, but different prediction results may be obtained based on different intervals in many cases. Figure 1 shows an example of three prediction results: upward movement (from early 1 minute to current time), highly volatile (from early 4 minutes to current time), and steady downward movement (from early 12 minutes to current time), which are obtained by current value with three different intervals. It shows that, traditional prediction methods based on a single fixed interval can not provide multiple prediction decisions simultaneously. That is, it can not satisfy the diverse requirements of different time terms. Therefore, it is necessary to provide multi-prediction results with multiple intervals.

The MIP is to predict the trend of a data stream based on various intervals of historical data. As shown in the example of Fig. 1, MIP can provide three prediction results simultaneously by choosing 1-minute, 4-minute and 12-minute intervals.

2.2 Prediction of Data Streams with HTM

The HTM is a machine learning model that replicates the structural and algorithmic properties of the neocortex. It is organized as a tree-shaped hierarchy of nodes, where each node implements a common learning and memory function [8].

A typical HTM network uses the Zeta1Node in the lower level for unsupervised learning. The

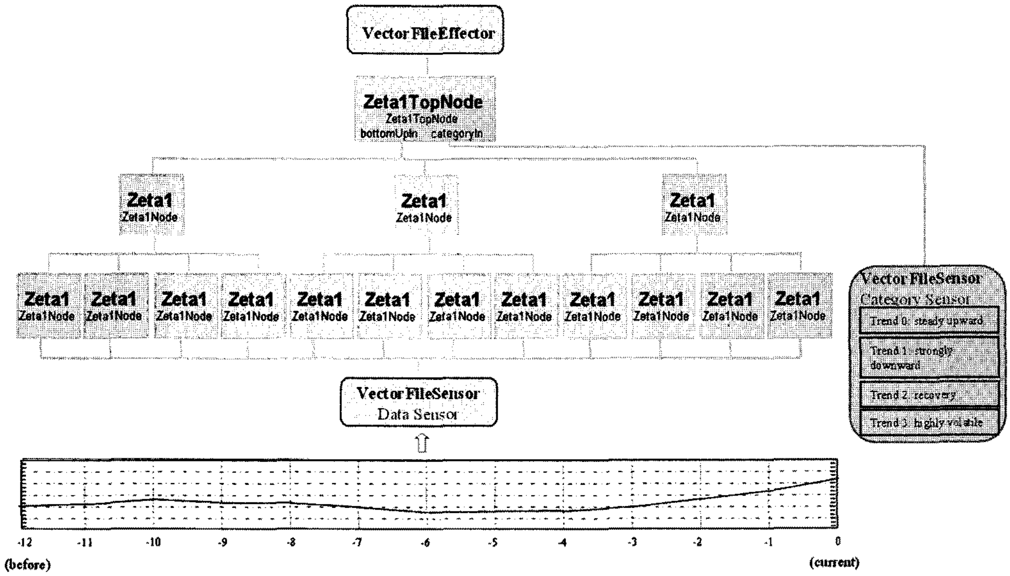

Fig. 2 An example of HTM network to prediction the trend of data streams with a fixed interval

Zeta1TopNode is used exclusively in the top level for supervised learning and generating prediction results based on the category information [9,10]. Hence, the HTM network can produce only one prediction result based on a fixed interval. Figure 2 shows a simple three level HTM network used to predict the trend of a data stream based on a fixed interval.

In Fig. 2, input to the network is a data stream of 12-minute intervals with time granularity as 1 minute. Each Zeta1Node at the bottom level receives input from the sensor. The input of each Zeta1Node at the bottom level corresponds to one 1-minute interval. The input of Zeta1Node at level 2 is the combination of results from the four child nodes which correspond to four 1-minute intervals, namely 4-minute intervals. The Zeta1TopNode at the top level covers the entire twelve 1-minute intervals, namely 12-minute intervals. The Zeta1-TopNode in the example shown in Fig. 2 performs supervised learning based on four trend categories: Trend 0 is a steady upward movement; Trend 1 is a strongly downward movement; Trend 2 is a recovery movement; Trend 3 is a highly volatile movement.

The HTM network works in two stages - training and prediction. During training stage, the HTM network learns to recognize patterns in the input data streams it receives. Each level in the network is trained separately. In the fully trained HTM network, the nodes in each level of the network form a model of data steams. During prediction, when the HTM network is presented with a new data stream, it can determine the likelihood that the data stream is one of the categories.

2.3 Problem of MIP with HTM

The HTM network can predict the trend of a data stream with a single fixed interval. In order to support multi-interval prediction, we have to make multiple HTM networks based on different intervals. Figure 3 shows an example of three HTM networks based on the three different fixed intervals.

In Fig. 3, network 1 processes a data stream with a 1-minute interval. Network 2 processes a data stream with 4-minute intervals. Network 3 processes a data stream with 12-minute intervals. The number of networks is proportional to the number of prediction intervals and the size of network is proportional to the length of the interval. Obviously, it is not easy to operate and manage the networks. Moreover, it will consume more memory and computation time.

We will give a solution to integrate multiple HTM networks using a new node type Zeta1LastNode.

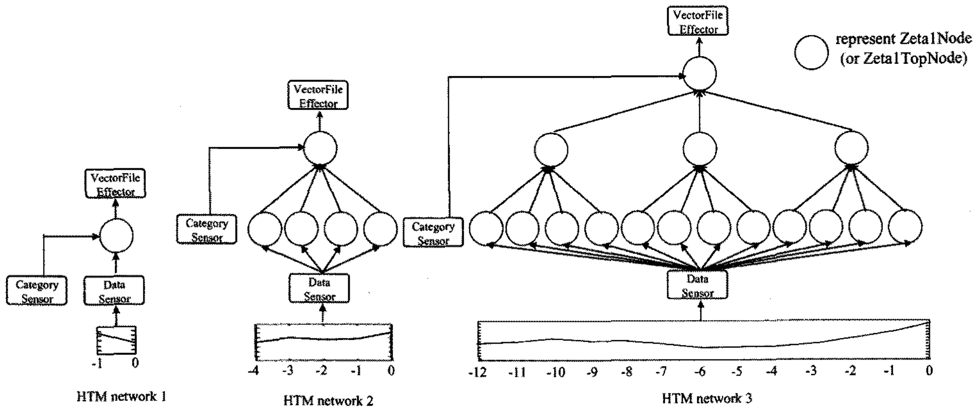

Fig. 3 Multiple HTM networks for the multi-interval prediction

3. Structure and Principle of Zeta1LastNode

Zeta1Node is used in the lower level for unsupervised learning in the original HTM network. The output of Zeta1Node is inputted to the upper level until it arrives at the Zeta1TopNode at the top level. Zeta1TopNode performs supervised learning and generates prediction results based on the category information. It means the original HTM network is restricted to process a single fixed interval as there is only one Zeta1TopNode.

In order to process multi-interval data and generate multiple prediction results, we propose a new node type, namely Zeta1LastNode. The Zeta1LastNode is the integration of the original HTM nodes Zeta1Node and Zeta1TopNode. As shown in Fig. 4, the Zeta1LastNode is composed of a spatial pooler, a temporal pooler and a supervised mapper. Thus it can perform both unsupervised and supervised learning. The spatial pooler, temporal pooler, and supervised mapper of Zeta1LastNode are nearly identical to the three modules of original HTM network.

Zeta1LastNode has two modes of operation, learning and inference. The Zeta1LastNode feeds the stream of input data to its spatial pooler in the learning mode in order to analyze the input data and generate a "coincidences matrix". This coincidences matrix quantizes the potentially huge space of input data into a relatively small, finite set of representative canonical input. These canonical input selected by the spatial pooler is named "coincidences". The output of spatial pooler is the coincidence indices which are sent to the temporal pooler and supervised mapper simultaneously. The temporal

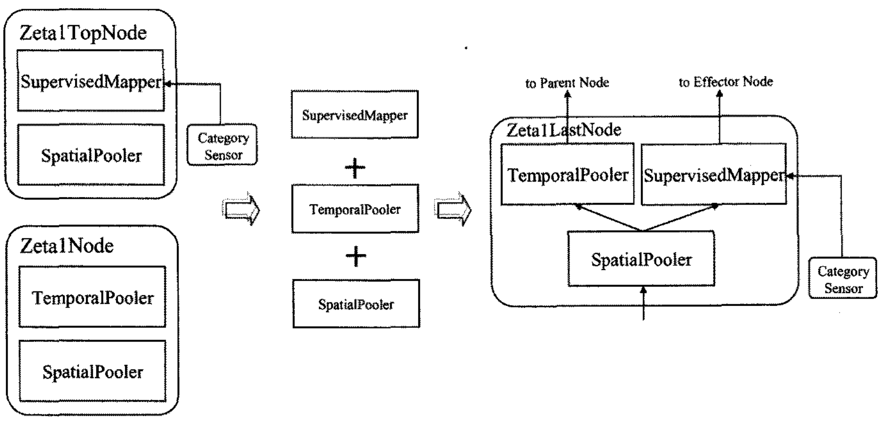

Fig. 4 Structure of Zeta1LastNode

pooler receives coincidence indices and keeps track of which coincidences occur close together in time. After completion of the learning stage, the temporal pooler forms the non-overlapping groups of coincidences, where each group contains the coincidences. Meanwhile, the supervised mapper receives coincidence indices and simply maps these coincidences to categories obtained from the category sensor.

The inference operation of Zeta1LastNode consists of identifying which temporal group the input data belongs to and generating a belief distribution over the categories. These two operations of Zeta1LastNode are the same as the original HTM node types that are Zeta1Node and Zeta1TopNode. During inference mode, the spatial pooler no longer updates the coincidences matrix. It compares each new input data with the coincidences to compute belief vector. The output of the spatial pooler is a vector which is a distribution over all the learnt coincidences. The output is handed off to the temporal pooler and supervised mapper. The temporal pooler uses its groups to convert the incoming belief vectors to distributions over groups, which becomes the input of the node at the higher level. The supervised mapper receives the belief vector from the spatial pooler and produces a distribution over categories, which is the output of the node.

4. IHTM Network for MIP

Now we present out IHTM network for MIP, where the Zeta1FirstNode plays an important role in training and prediction stage.

4.1 Structure of IHTM Network

Figure 5 shows an example structure of the IHTM network, which integrates three HTM networks. The network has three types of nodes (Zeta1Node, Zeta1LastNode, and Zeta1TopNode), together with VectorFileSensor, and VectorFileEffector. There is only one Zeta1LastNode in each level. The Zeta1LastNode is located in the last position, where the remaining locations use the Zeta1Node. The top level has and only has one Zeta1TopNode.

In Fig. 5, a data stream is input to the network and fed to the specified nodes at the bottom level. The input to the network is a data stream of 12-minute intervals with time granularity as 1 minute. The data items in the data stream recorded every other interval are inputted to the corresponding node at the bottom level of the network. The

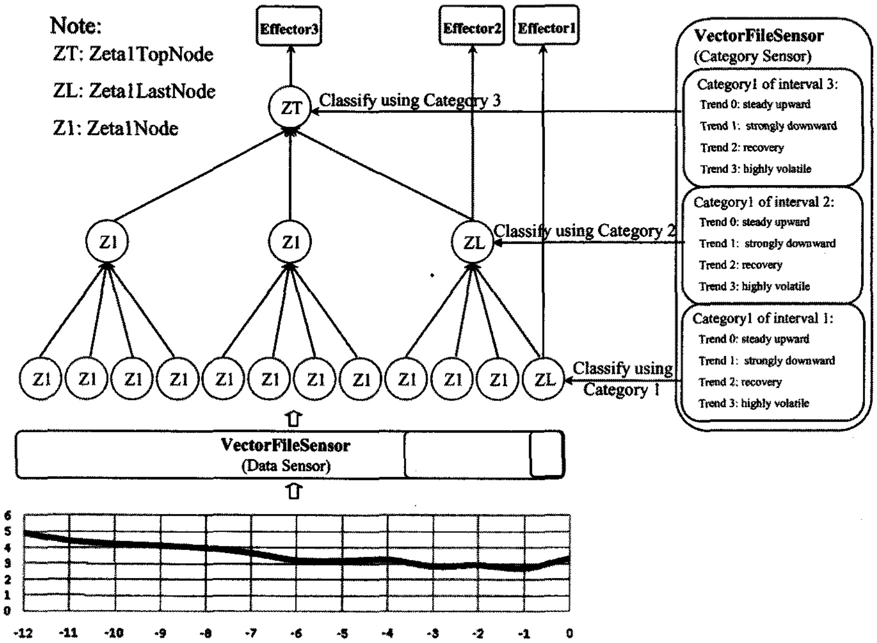

Fig. 5 IHTM network for multi-interval prediction

nodes at higher level receive the input from one or more child nodes at lower level. Therefore, the interval length of input data for the node increases as it goes up along the hierarchy. In Fig. 5, the input to the node at level 2 covers 4-minute intervals. The Zeta1TopNode at the top level covers the entire 12-minute intervals.

The Zeta1LastNode and the Zeta1TopNode are used to perform supervised learning and prediction. They receive the input data from VectorFileSensor (Data Sensor) or child nodes. They also receive category information from the VectorFileSensor (Category Sensor).

The output of Zeta1LastNode and the Zeta1TopNode are received by the VectorFileEffector at the corresponding level for generating the multi-interval prediction results.

4.2 Operation of IHTM Network

The IHTM network is operated in two distinct stages — training and prediction.

A. Training Stage

The IHTM network performs training similar to the original HTM network, namely level by level training. In order to perform faster training, we let only Zeta1LastNode at each level perform supervised learning. The data structures of Zeta1LastNode are copied later to the other nodes at the same level. Figure 6 shows the network used for MIP during training stage.

In the first step of training shown in Fig. 6①, only the Zeta1LastNode at level 1 is enabled and put into learning mode. It receives the stream of learning data of 1-minute intervals directly from the Data Sensor. This input goes directly to the spatial pooler. The spatial pooler finds coincidences in its input. The output of spatial pooler is the coincidence indices which is sent to the temporal pooler and supervised mapper simultaneously. The temporal pooler receives coincidence indices and classifies adjacent coincidences into the same group. Meanwhile, the supervised mapper uses the category indices from the category1 sensor simply to map the coincidence indices to categories. After all the learning data has been presented, the node structures of the spatial pooler and temporal pooler in the Zeta1LastNode are copied to the Zeta1Node at the same level.

In the second step of training shown in Fig. 6②, a single Zeta1LastNode at level 2 along with its children in level 1 are enabled. The Zeta1LastNode

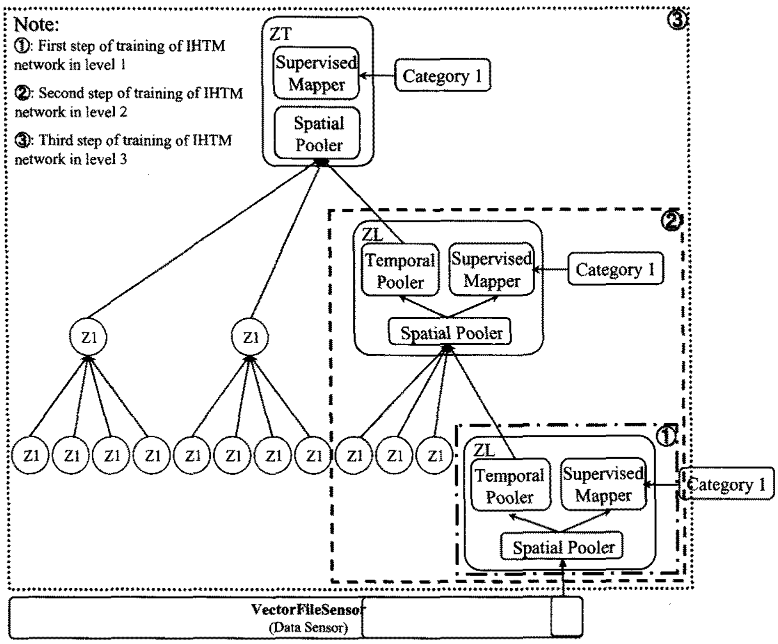

Fig. 6 IHTM network for training

at level 2 is put into learning mode and its children in level 1 are put into inference mode. In Fig. 6②, there are four child nodes to receive inference data from the Data Sensor, respectively. The outputs of these four child nodes are combined and become the input of the ZetalLastNode at level 2. The ZetalLastNode at level 2 receives this input data of 4-minute intervals from its four child nodes and performs learning as the ZetalLastNode did at level 1. After ZetalLastNode at level 2 has learnt all the learning data, the node switches to inference mode and the data structures are copied to the remaining ZetalNode at level 2 as described above.

This procedure is repeated up throughout the hierarchy until all the nodes in the network are enabled. As shown in Fig. 6③, the Zeta1TopNode at top level is put into learning mode. Its three child nodes at level 2 and twelve grandchild nodes at level 1 are put into inference mode. The inference output of the nodes at level 1 is sent to nodes at level 2, and then the inference output of the nodes at level 2 is sent to the Zeta1TopNode as learning data. The Zeta1TopNode is trained using the data stream with 12-minute intervals.

B. Prediction Stage

During the prediction stage, all nodes at each level are enabled and the network is exposed to new data streams with 12-minute intervals. At the end of the prediction stage, the prediction results based on 1-minute, 4-minute and 12-minute intervals are generated by the ZetalLastNode at level 1, level 2 and the Zeta1TopNode at top level. Figure 7 shows the IHTM network for multi-interval prediction.

In Fig. 7, the ZetalLastNode and ZetalNode at level 1 receive the sequence of vectors with 12-minute intervals from the VectorFileSensor as [v_{-12}, v_{-11}, v_{-10}, v_{-9}, v_{-8}, v_{-7}, v_{-6}, v_{-5}, v_{-4}, v_{-3}, v_{-2}, v_{-1}]. The input data v_i at t_i is the value difference from t_{i-1} to t_i. For instance, if the value is 8.01 at t_{i-1} and the value is 8.12 at t_i, then the difference value in

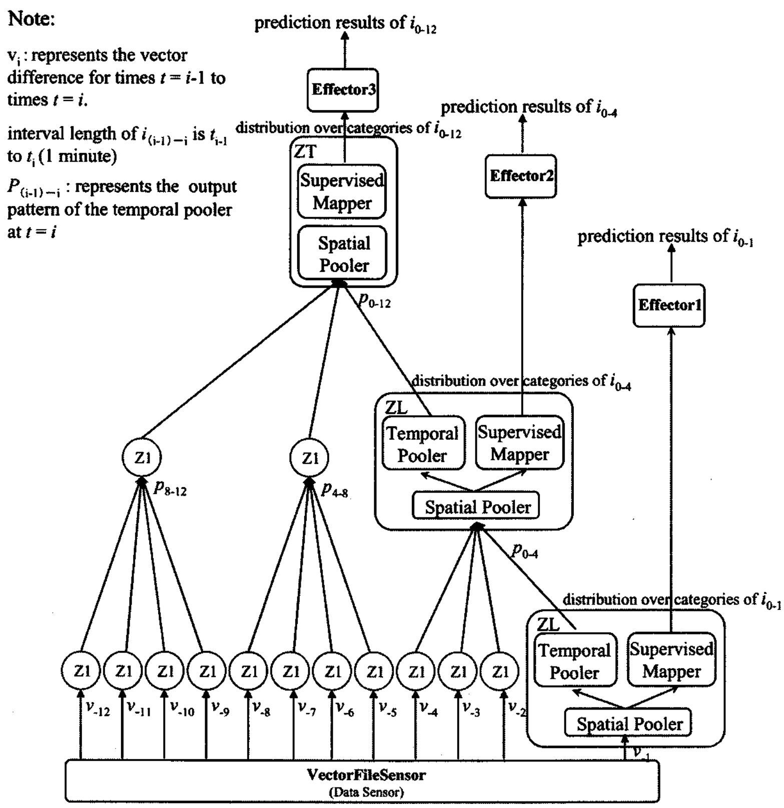

Fig. 7 IHTM network for prediction

the interval $i_{(i-1)-i}$ from t_{i-1} to t_i, v_i is +0.11. The spatial pooler of each node at level 1 receives its corresponding input. It compares this input vector to each coincidence learnt during training stage and computes a belief vector for its input vector. This belief vector is sent to the temporal pooler. The temporal pooler receives this belief vector and calculates belief distribution over groups of $i_{(i-1)-i}$ which is marked as $p_{(i-1)-i}$. The $p_{(i-1)-i}$ is a vector which has the same size as the number of temporal groups. For example, the node has 12 coincidences within its spatial pooler and has 4 temporal groups within its temporal pooler. Present input matches the fourth coincidence which belongs to the temporal group 2. Therefore, the output of the temporal pooler $p_{(i-1)-i}$ is a vector of 4 groups with 1 match corresponding to group 2 and represented as [0100]. Meanwhile, the supervised mapper of the Zeta1LastNode receives the belief vector from the spatial pooler and produces a distribution over categories as the 1-minute interval prediction result of level 1.

The Zeta1LastNode at level 2 receives its input data from its four child nodes, three Zeta1Nodes and one Zeta1LastNode at level 1. The input is the data pattern of interval i_{0-4}. The temporal pooler generates its result p_{0-4}. This output is concatenated with the output of two other brother Zeta1Nodes for uploading the pattern information p_{0-12} to the Zeta1TopNode. The supervised mapper of this node produces the distribution over categories of i_{0-4} as the 4-minute intervals prediction result of level 2.

The Zeta1TopNode at level 3 receives its input data from its three child nodes, two Zeta1Node and one Zeta1LastNode at level 2, which is the pattern information of input data of the interval i_{0-12}, and produces a 12-minute intervals prediction result.

5. Performance Evaluation

The IHTM network is efficient in reducing memory and time consumption compared with the original HTM network in MIP. The analysis is based on the original HTM network shown in Fig. 3 and IHTM network shown in Fig. 5.

5.1 Comparison of Memory Consumption

The original HTM network needs multiple networks to achieve MIP and consumes more memory. The number of original HTM networks increases proportionally with the number of prediction intervals. However, the IHTM network can support MIP using only one network. So pretty much we can reduce the amount of memory. This is very advantageous for the operation of the system.

The memory consumption of the original HTM network with n intervals prediction, denoted by Mo, and the IHTM network with n intervals prediction, denoted by Mi, are represented by the following equations:

$$Mo = \sum_{i=1}^{n} mo_i = \sum_{i=1}^{n} ni_{Z1} \times n_{Z1} + m_{ZT}$$

$$Mi = n_{Z1} \times m_{Z1} + n_{ZL} \times m_{ZL} + m_{ZT}$$

where mo_i is the memory consumption of the ith original HTM network, n_{iZ1} is the number of Zeta1-Nodes in the ith HTM network, m_{Z1} is the memory consumption of one Zeta1Node, and m_{ZT} is the memory consumption of one Zeta1TopNode, n_{Z1} is the number of Zeta1Nodes in the IHTM network, n_{ZL} is the number of Zeta1LastNodes in the IHTM network, and m_{ZL} is the memory consumption of one Zeta1LastNode.

Based on experimental measurements, the average memory consumption of one Zeta1Node is nearly equal to that of the Zeta1TopNode. The average memory consumption of one Zeta1LastNode is almost 1.5 times higher than the Zeta1Node. Using the above equation, let n be 3, we calculate that $mo_1 = n_{1Z1} \times m_{Z1} + m_{ZT} = 0 + m_{ZT} = m_{Z1}$, $mo_2 = n_{2Z1} \times$

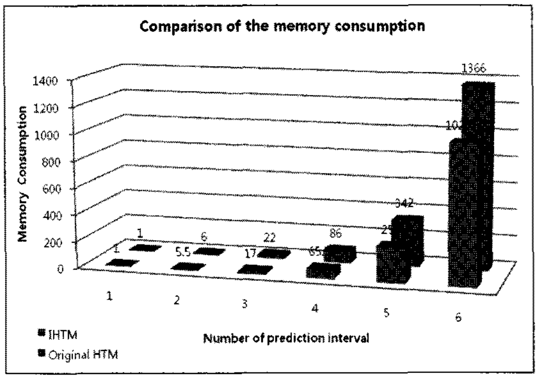

Fig. 8 Comparison of the memory consumption of the original HTM network and the IHTM network

$m_{Z1} + m_{ZT} = 4 \times m_{Z1} + m_{ZT} = 5m_{Z1}$, and $mo_3 = n_{3Z1} \times m_{Z1} + m_{ZT} = 15 \times m_{Z1} + m_{ZT} = 16m_{Z1}$. Therefore, the memory consumption of the original HTM network is $Mo = mo_1 + mo_2 + mo_3 = m_{Z1} + 5m_{Z1} + 16m_{Z1} = 22m_{Z1}$. The memory consumption of IHTM network is: $Mi = n_{Z1} \times m_{Z1} + n_{ZL} \times m_{ZL} + m_{ZT} = 13 \times m_{Z1} + 2 \times m_{ZL} + m_{ZT} = 17m_{Z1}$. Fig. 8 shows that the original HTM network consumes much more memory than the IHTM network while the number of prediction intervals increases.

5.2 Comparison of Time Consumption

Besides memory consumption, the time consumption of the IHTM network is much lower than the original HTM network in prediction.

The total time consumption of prediction with the original HTM network and the IHTM network with n intervals are modeled via the following equations:

$$To = \sum_{i=1}^{n} to_i = \sum_{i=1}^{n} n_{iZ1} \times t_{Z1} + t_{ZT}$$

$$Ti = n_{Z1} \times t_{Z1} + n_{Z1} \times t_{ZL} + t_{ZT}$$

where to_i is the time consumption of the ith original HTM network, n_{iZ1} is the number of Zeta1-Nodes in the ith HTM network, t_{Z1} is the time consumption of one Zeta1Node, and t_{ZT} is the time consumption of one Zeta1TopNode; n_{Z1} is the number of Zeta1Nodes in the IHTM network, n_{ZL} is the number of Zeta1LastNodes in the IHTM network, t_{ZL} is the time consumption of one Zeta1LastNode.

Based on experimental measurements, the average time consumption of prediction of one Zeta1Node is equal to that of the Zeta1TopNode. The average time consumption for prediction of one Zeta1Last-Node is almost 1.4 times higher than the Zeta1-Node. Using the above equation, let n be 3, we calculate that $to_1 = t_{ZT} = t_{Z1}$, $to_2 = n_{2Z1} \times t_{Z1} + t_{ZT} = 4 \times t_{Z1} + t_{ZT} = 5\ t_{Z1}$, and $to_3 = n_{3Z1} \times t_{Z1} + t_{ZT} = 15 \times t_{Z1} + t_{ZT} = 16\ t_{Z1}$. Therefore, the time consumption of the original HTM network is $To = to_1 + to_2 + to_3 = t_{Z1} + 5t_{Z1} + 16t_{Z1} = 22t_{Z1}$. The time consumption of the IHTM network is: $Ti = n_{Z1} \times t_{Z1} + n_{ZL} \times t_{ZL} + t_{ZT} = 13 \times t_{Z1} + 2 \times t_{ZL} + t_{ZT} = 13 \times t_{Z1} + 3 \times t_{Z1} + t_{Z1} = 17t_{Z1}$. As shown in Fig. 9, the result indicates that the IHTM network is significantly better in time consumption than the original HTM network for MIP with the increase of the number of prediction intervals. Accuracy of the

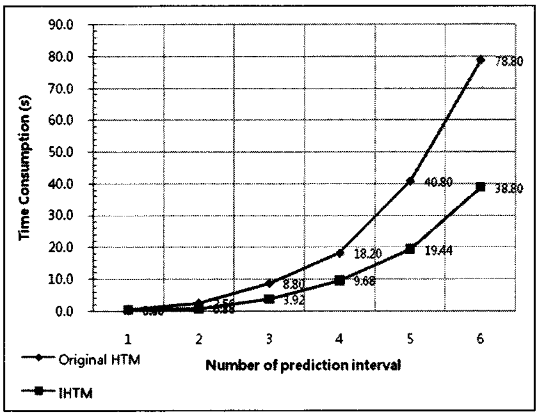

Fig. 9 Comparison of the time consumption of the original HTM network and the IHTM network

prediction was the same result as the original HTM network.

6. Conclusion and Future Research

In this paper, we present the multi-interval prediction (MIP) for data streams. The MIP attempts to predict the trend of a data stream based on various intervals of historical data according to different requirements. We believe that MIP is a crucial problem in the trend prediction of data streams.

We proposed an IHTM network to solve the problem of MIP for data streams. The IHTM is constructed by introducing a new node type Zeta1-LastNode to the original HTM network. Using the IHTM network, we can overcome the limitation of the original HTM network and achieve a higher flexibility on the MIP problem. The performance evaluation shows our approach is feasible for processing data streams with multi-intervals.

In the real world, the MIP for data streams can be applied in various domains, such as analyzing airplane performance, diagnosing diseases, stock price trend prediction amongst others. Future studies are expected to apply MIP to these applications.

References

[1] Y. Yang, X. Wu, and X. Zhu, "Proactive-reactive prediction for data streams," *Technical Report CS-05-03*, Department of Computer Sciences, University of Vermont, USA, 2005.

[2] B. Babcock, S. Babu, M. Datar, R. Motawani, and J. Widom, "Models and issues in data stream systems," *In ACM Symposium on Principles of Database Systems (PODS)*, 2002.
[3] H. Wang, W. Fan, P. Yu, and J. Han, "Mining Concept-Drifting Data Streams Using Ensemble Classifiers," *SIGKDD'03*, Washington, 2003.
[4] Numenta, Numenta HTM Home page, *Numenta Inc*, 2007. http://numenta.com/.
[5] J. Hawkins and D. George, "Hierarchical Temporal Memory: Concepts, Theory, and Terminology," *Numenta Inc*, 2006.
[6] Numenta, waves example, *Numenta Inc*, 2007.
[7] Numenta, wallstreet example, *Numenta Inc*, 2007.
[8] D. George and B. Jaros, "Zata1 Algorithms Reference," *Numenta Inc*, 2007.
[9] D. George and B. Jaros, "The HTM Learning Algorithms," *Numenta Inc*, 2007.
[10] D. George, "How the Brain Might Work: A Hierarchical and Temporal Model for Learning and Recognition," doctoral dissertation, Stanford University, June 2008.

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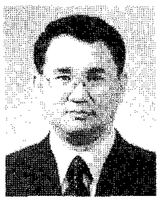

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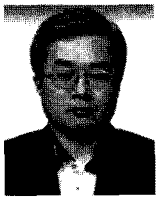

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