A Rough Neural Network Algorithm for Multisensor Information Fusion

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Abstract

The multisensor information fusion is a key issue for multisensor system. One of its difficulties lies in the switching of the state of sensor clusters. That is, which direction should the sensor information been fused into at a given moment? An algorithm of multisensor information fusion based on rough set and neural network was proposed in this paper. Firstly, the typical clustering distributions of 54 sensors within one day were regarded as sample space. The rough set was used for access of knowledge to make the decision table of the "data-fusion distribution". Next, the redundant properties and samples of information in one month were removed using the method of knowledge reduction of rough set. Then, the neural network was applied for clustering and analyzing to form the distribution rules of multisensor information fusion. Finally, the rough neural fusion algorithm, the neural quotient space fusion algorithm and word computing fusion algorithm are simulated and analyzed. The results show that the model and algorithm proposed in the paper are efficient in classification and rapid in sensor clustering distribution decide.

Keywords: rough set, neural network, data fusion, sensor network, Tossiom

1. Introduction

The multisensor information fusion is a key issue for multisensor system. This class of problem has received considerable attention in wireless sensor network because multisensor information fusion is an effective method to reduce the network communication data amount and extend the survival time of sensor network. EdwardWaltz and James Linas give the following definition: "information fusion is a multi-level and multi-aspect data proceeding process. The process can get accurate state and identity estimation, complete and timely estimate situation assessment and threats through dealing with the detection, relevance, related, estimation and combination of multi-source data." [1]

The main techniques of information fusion include pattern recognition, decision-theory, uncertainty theory, signal processing, estimation theory, optimum technology, artificial intelligence and neural network [2, 3], etc. The methods of information fusion based on neural network [4] are more common now. But, through researching the current multi-sensor information integration system based on neural network, it is found that the common faults of the systems is: when the amount of data from sensor is large and/or the network structure is huge, neural network's training time becomes too long and network training has heavy burden, the performance of the system will be big reduced.

Due to the advantage of the rough set in dealing with redundant data, large amount of data and uncertain data, more and more scholars pay more attention to the combination of rough set and the neural network [5, 6]. Pre-processing data using rough set can simplify the neural network training samples and speed up the training speed. This kind of method of combination of rough sets and neural network has been used in the industry [7-9], agriculture [10], financial [11] and other fields.

The differences between this paper and the literatures mentioned above are: (1) The experiment environment of this paper is a sensor network of 54 sensors. The network is more complex and sensor data amount is larger than the literatures mentioned above. (2) This paper
firstly connected ART2 neural network to rough set. (3) This paper is an explicit instantiation of integrating ART2 neural network and rough set based on the modificative actual TinyOS network protocol stack, and the added OS data fusion layer can be directly transplant to the actual system.

2. Sensor network entity

We choose 54 Mica2Dot sensor data in inter Berkeley Research lab from February 28 to April 5 in 2004 to do the simulation in TOSSIM. Sensors layout is shown in Figure 1.

![Fig.1 Sensors layout](image)

During this period of time each sensor will send data packets which contain humidity, temperature, light and voltage values every 31 seconds. It totally produces 23 million data of about 150 MB file. Data is shown in Table 1. In these data, the temperature unit is Celsius. The range of relative humidity corrected by temperature is from 0 to 100%. The light unit is lux. (1 lux is equivalent to moonlight strength, 400 luxs are equivalent to a bright office and 100000 luxs are equivalent to the strength of the direct sunlight). The voltage unit is volts ranging from 2 to 3 volts. Usually, lithium-ion batteries used in sensors is to keep a stable voltage which the voltage value is correlated with the temperature.

### Table 1 data structure

<table>
<thead>
<tr>
<th>Date:yyyy-mm-dd</th>
<th>Time:hh:mm:ss:xx</th>
<th>Epoch:int</th>
<th>Mote:int</th>
<th>Temperature:real</th>
<th>Humidity:real</th>
<th>Light:real</th>
<th>Voltage:real</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004-03-14</td>
<td>00:00:43.286014</td>
<td>43085</td>
<td>1</td>
<td>21.4878</td>
<td>40.9392</td>
<td>16.56</td>
<td>2.5166</td>
</tr>
<tr>
<td>2004-03-14</td>
<td>00:00:06.412148</td>
<td>43084</td>
<td>2</td>
<td>21.723</td>
<td>41.9818</td>
<td>39.56</td>
<td>2.4954</td>
</tr>
<tr>
<td>2004-03-14</td>
<td>00:00:36.271604</td>
<td>43085</td>
<td>2</td>
<td>21.7034</td>
<td>42.0489</td>
<td>37.72</td>
<td>2.4954</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. The data of the rough reduction

An information system can be expressed as $S=(U,A)$. Here, $U$ and $A$ are limited and non-empty collections, $U$ is a set of objects called domain, and $A$ is the collection of properties. Any a subset $(B)$ of $A$ can establish a binary relationship under $U$. Gens equivalent category means a classification of $B$, which will be expressed as $U/I(B)$ or simple expressed as $U/B$. An equivalent category $I(B)$ is the division of $U/B$, in which the block contains $x$ will be expressed $B(x)$ called the area of the group $B$ containing $x$. If $(x, y)$ belong to $I(B)$, $x$ and $y$ is in no distinguish in $B$.

Many properties are repeated and redundant to classification. The definition of reduction is the correct classification and minimum attributes set which not contain any redundant attribute. That is, when there is a property that $b \in B$, equivalent relation $B$ belongs to $A$ can make the equation $U/B=U/(B-b)$ established and we can say that $b$ can be omitted in $B$ or we may say $b$ can not be omission in $B$. If $b$ can be omitted in $B$, make $B=B-r$. When there is no attributes can be omitted in $B$, it is said that $b$ is independent. And you will get a reduction of $B$ noted as $red(B)$.
Data of adjacent nodes in network has similar features and there is a lot of complementary redundant information. Data packets sent from same sensor in a short time also have redundant. According to the research from Govindan shows that in random area s which distribution density is \( p(x, y) \), sensor redundant data between the nodes is \( \eta = \xi S_d \).

During the process of the rough set, we make humidity, temperature, light, voltage data in different time as the sample space and choose the typical data to form condition attributes. One sensor can constitute the decision attribute of rough set when the sensor can represent a group of sensors in a time range. Discernibility matrix is constructed on the basis of decision table. The discernibility matrix is a very important concept in the rough set theory. It will concentrate the information of distinguishing attribute from decision table into a matrix, and can be used in solving the reduction and core of decision table. That is, the core affects the key attributes of representing sensor. The key attributes of light and temperature of 54 sensors in 24 hours after rough processing was expressed in Figure 2 and Figure 3 respectively.

![Fig.2 The key attributes of the light](image1)
![Fig.3 The key attributes of the temperature](image2)

### 4. Neural network clustering

#### 4.1 Rough set-ART2 network and clustering

Remove the no influence properties of representative sensor and remake new decision table. If it is already the simplest decision table, it can be directly into the next training step of neural network. Take typical sensor data which consist of the reduced condition attributes as the samples and send them to neural network for clustering.

ART2 network is a self learning neural network, and it has good clustering capability. In ART2 network [12], the choice of vigilance parameters \( \rho \) decides the delicate degree of classification. When \( \rho \) is a big value, the classification conditions are strict and the classification number is large. And when \( \rho \) is a small value, the classification of pattern is rough and the classification number is small.

The structure of rough set-ART2 network is shown in Figure 4. It has two parts of noticed subsystem and adjusting subsystem. Noticed subsystem consists of feature expressing field \( F_1 \), category expressing field \( F_2 \) and the long-term memory coefficient \( LTM \) between field \( F_1 \) and field \( F_2 \). The \( F_1 \) is input and comparison layer. And the same time, it also is the core of the whole system and the entrance that the rough set processes results. The \( F_2 \) is recognition layer and completes competitive learning of each neuron. Adjusting subsystem is composed by reset institution.

In the sensor clustering, it can cause the wrong classification if the warning coefficient makes bigger, which will cause an excessive reduced precision to the sensor data. If the warning coefficient is small, it will cause the large number of classification and can't well meet the purpose to reduce the amount of transmission data.

After the test, it is the most ideal result when \( \rho = 0.9720 \) is chosen. When 15524 samples have been input for clustering analysis, the classes are divided into 27 finally. In Fig.5 and Fig.6, it was shown fusion classification layout diagrams of the first kind of sensors and the 27\(^{th}\) kind of sensors respectively.
4.2 Data fusion layer protocol

In practice when applying the algorithm described above, we need to add data fusion layer in sensor protocols. The data fusion layer is mainly used for multisensor information fusion in the network such as association, group, classification, statistics, and the information would be fused into export forwarding messages sent to the next hop with much smaller bit streams and more certainty. So the functions to recognize and estimate perception objects can be achieved ultimately. The data fusion layer of forwarding node will fuse the multiple sets of perception information received from its lower layer called network layer, and put the fused results to its lower layer to forward. For nodes only used for perception, they will fuse perception information and their own historical data.

TinyOS [13] is specifically designed according to the features of sensor network by the University of California, Berkeley. TinyOS uses high efficient executive mode based event, and includes a specially designed formation model, thus become a component-application software which is efficient, modular and easy to construct. In TinyOS, application developers can express...
the event or command interfaces between one component and another using nesC language. Components are divided into configuration files and modules, and program flow is built through the connection of the interface in the configuration file while specific implementation of logic functions is done through the module. Each module is composed of a set of commands and events called the interface of the module. In General, the upper components send commands to the lower components, and the lower components signal the event occurs, then the components at the bottom interact with hardware directly, so as to form a tree structure from top to bottom. Therefore, the specific method to add network hierarchical structure of data fusion layer to TinyOS network protocol stack is to add routing module and data fusion module in TinyOS as well as to modify the communications module code. The structure of improved communication protocol stack is shown in Figure 7.

![Figure 7. The structure of improved communication protocol stack](image)

5. Simulation test

In order to evaluation of the performance of data fusion layer directly, TOSSIM simulator [14, 15] attached to TinyOS simulates the network operation states in the before and after improvement of protocol stacks respectively. The simulation compiler can compile simulation program through the application of TinyOS directly, for TOSSIM runs the same code with the sensor hardware. TOSSIM changes hardware interrupt for discrete event, the interruption of the event drives out the upper applications by simulation system and the other TinyOS components especially upper application components do not need to change through replacing the related components of lower part of TinyOS. The operating model of sensor is controlled by using Python language, and the working program of the sensor is shown in Figure 8.

![Figure 8. The Python control sensor program](image)

The contrast situation of network to the amount of sending and receiving data packets is shown in Figure 9. In the chart, it can be seen that the data quantity of sensor sending and receiving is obviously reduced after using the polymerization of rough-ART2 and it has better fusion result than the fusion algorithm of quotient space [16, 17] and the fusion algorithm of word computing [17, 18]. Because the sensor network energy consumption is mainly used in sending and receiving the data packets, sensor information transmission costs more electricity energy than calculation. The electricity for sensor transmission 1 bit information can execute thousands of calculation instructions. And the energy consumption of communication relates to the distance for transmission and it is cubic equation to distance. Obviously, it can eventually
save the energy consumption of the whole sensor networks through reducing unnecessary data transmission.

By calculating the average fusion degree (the total amount of sending data after the fusion / the total amount of data being sent) and the eventual fusion variance of various data, the results were listed in Table 2. According to Fig.10 and Table 2, the fusion algorithm of word computing is the worst in the effect on the amount of data reduction because it is controlled to generate fusion distribution. If the number of fusion to generate distribution is increased, the better fusion results can be get, but the fusion speed is reduced. While after the accumulation in the first several days, rough set and quotient space had improved significantly their data reduction capability, and their fusion effect is very good. As quotient space handed topology to convergent central node, its fusion effect is relatively poorer than rough set, but its operation speed is faster than rough set.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Fusion (%)</th>
<th>Temperature Var (°C)</th>
<th>Humidity Var (%)</th>
<th>Light Var (lux)</th>
<th>Voltage Var (V)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rough neural network</td>
<td>59.33</td>
<td>0.242</td>
<td>0.422</td>
<td>4.49</td>
<td>0.02</td>
</tr>
<tr>
<td>Quotient neural network</td>
<td>68.35</td>
<td>0.242</td>
<td>0.421</td>
<td>4.57</td>
<td>0.02</td>
</tr>
<tr>
<td>Word compute</td>
<td>89.72</td>
<td>0.138</td>
<td>1.126</td>
<td>3.33</td>
<td>0.02</td>
</tr>
</tbody>
</table>

6. Conclusion

In this paper, the experimental environment is the sensor network composed of 54 sensors. The network is relatively complex and the other neural networks should not take comparative simulation because of the lack of ART2 clustering features. Compared to quotient space fusion algorithm and word computing fusion (see in Fig.10), it can be seen the fusion algorithm of rough-ART2 in the paper has the obvious advantages in the fusion degree.

To sum up, the rough set combined efficiently with ART2 network has greater advantages in the multi-sensor data fusion. In the actual application, if the agreement layer is added in OS of the sensor, it can greatly reduce the amount of sensor data transmission. The problem of single sensor fusion direction solves well in data fusion. Although there are some shortcomings such as summarizing the sample of network fusion structure is harder, the request of processing sensor data is higher and so on, it is trusted these problems can be well resolved in the near future with the continuous improvement of technology of the sensor hardware.
References


