State Recognition and Visualization of Hoisting Motor of Quayside Container Crane Based on SOFM

Z.Q. Yang\textsuperscript{1a}, P. He\textsuperscript{2b}, G. Tang\textsuperscript{1c}, X. Hu\textsuperscript{1d}

\textsuperscript{1}Logistics Engineering College, Shanghai Maritime University, 1550 Harbor Road, Pudong New Area, 201306, Shanghai, China
\textsuperscript{2}Shanghai East Container Terminal, 200137, Shanghai, China
\textsuperscript{a}youngzhiqi111@163.com, \textsuperscript{b}hep@sect.com.cn, \textsuperscript{c}gangtang@shmtu.edu.cn, \textsuperscript{d}huxiong@shmtu.edu.cn

Abstract. The neural network structure and algorithm of self-organizing feature map (SOFM) are researched and analysed. The method is applied to state recognition and visualization of the quayside container crane hoisting motor. By using SOFM, the clustering and visualization of attribute reduction of data are carried out, and three kinds motor states are obtained with Root Mean Square (RMS), Impulse Index and Margin Index, and the simulation visualization interface is realized by MATLAB. Through the processing of the sample data, it can realize the accurate identification of the motor state, thus provide better monitoring of the quayside container crane hoisting motor and a new way for the mechanical state recognition.

1. Introduction
Before mining monitoring information of the quayside container crane hoisting motor, the priori knowledge of the data often fails to be gained. A state-recognition which is actually clustering analysis problem is an effective method, and unsupervised learning clustering algorithm is used to solve the problem.

The state recognition of multi-feature parameters of quayside container crane hoisting motor can obtain the sample data through multiple sensors to form a multi-dimensional space, and then the data is reduced and recognized to the low-dimensional space. In this mapping process, the low-dimensional space mapping should preserve and highlight the main properties in the original high-dimensional data, and thus to improve the accuracy of motor state recognition.

2. High-dimensional data visualization and its methods
High-dimensional data usually refers to the variable form that is \( F=f \left( x_1, x_2, L, x_N \right) \). For example, there are N monitoring points in the quayside container crane hoisting motor, and each monitoring point has 9 eigenvalues to form the N multiplied 9 dimensional data. Visualization of high dimensional data is mostly realized by dimensionality reduction, Linear or nonlinear methods can be used to transform high-dimensional space into two-dimensional or three-dimensional space that human can perceive\textsuperscript{[1]}. The SOFM algorithm is an unsupervised clustering method. The network can repeat the learning of the input pattern so that the probability distribution of the connection weight vector is consistent with the input pattern. It has two layers of network\textsuperscript{[2][6]}, one input layer, the other layer includes the competition layer and the output layer, and there are two typical structures including one-dimensional linear array and two-dimensional linear array.
3. Clustering Analysis of Mechanical State of the quayside container crane hoisting motor

3.1 Data reduction.

In the monitoring of the hoisting motor, several acceleration sensors are placed, and nine characteristic values are extracted from the collected signals, such as Square root amplitude of the vibration velocity, the effective value, the skewness index, the kurtosis index, the peak value index, the pulse index, the margin index and the variance index. Taking 28 days data of the quayside container crane hoisting motor, the relevant characteristic data are obtained, and 4000 samples of the data are collected every day to be analyzed and visualized. The following results are obtained by attribute approximation and normalization.

| Time | Margin index | RMS       | Pulse index |
|------|--------------|-----------|-------------|
| 1    | -0.75619     | 0.77337   | -0.97058    |
| 2    | -0.52976     | 0.78704   | -0.93672    |
| 3    | -0.54628     | -1.00000  | -0.47828    |
| 4    | -0.70062     | 0.47155   | -0.95843    |
| 5    | -0.42726     | 0.46136   | -0.91232    |
| 6    | -0.27790     | -0.04987  | -0.68793    |
| 7    | -0.62404     | 0.73640   | -0.93803    |
| 8    | -0.57819     | 0.54370   | -0.93822    |
| 9    | -0.41272     | 0.50735   | -0.88982    |
| 10   | -0.23475     | 0.27405   | -0.77565    |
| 11   | -0.89796     | -0.97168  | -0.85472    |
| 12   | 0.15387      | 0.03130   | -0.69016    |
| 13   | -0.47880     | 1.00000   | -0.94729    |
| 14   | -0.52498     | 0.26793   | -0.86347    |
| 15   | -0.65586     | 0.56287   | -0.91602    |
| 16   | -0.66216     | 0.93173   | -0.98850    |
| 17   | 1.00000      | -0.83678  | 1.00000     |
| 18   | 0.35139      | -0.81156  | 0.19050     |
| 19   | -1.00000     | -0.96401  | -1.0000     |
| 20   | -0.10624     | 0.15986   | -0.78445    |
| 21   | -0.61372     | 0.50796   | -0.91464    |
| 22   | -0.50187     | 0.46266   | -0.89533    |
| 23   | -0.24473     | 0.49439   | -0.83101    |
| 24   | -0.49887     | 0.54367   | -0.90312    |
| 25   | -0.01591     | -0.13438  | -0.58409    |
| 26   | -0.15392     | 0.30469   | -0.79925    |
| 27   | -0.45777     | 0.33085   | -0.87283    |
| 28   | -0.40532     | -0.08769  | -0.70611    |

The SOFM algorithm is realized by MATLAB. The topological structure of the network is constructed and selected. Six topological structures are constructed. The order of neurons is $1 \times 3, 2 \times 3, 3 \times 3, 4 \times 5, 4 \times 7$. $\eta(t) = 0.1$ Each network structure achieves a certain number of training, so that the network structure tends to be stable after training. From the training topology of network and output results, some neurons can’t be fully utilized, when there are too many neurons. In order to achieve more accurate network mapping, the appropriate neuron structure needs to be selected. The data can be divided into 3 to 9 kinds. In order to express it more accurately, the network topology arranged $3 \times 3$ is selected for data analysis.
3.2 Data clustering results.

After normalization of the reduced data, the SOFM algorithm is used to deal with it with \(\eta(t) = 0.1\) and the number of training \text{net.trainParam.epochs} = [100 500 1000 2000 3000 4000] is tested in Fig.1.

![Figure 1. Network topology after different training epochs](image)

To avoid over-fitting, as can be seen from the figure above, the network topology of 3000 training is selected, and then deal with the data. \(\eta(t) = 0.1\) Figure 4 and Table 2 are obtained.

![Figure 2. Topology of training network](image)

| Time | A | B | C | D | E | F | G | H | I |
|------|---|---|---|---|---|---|---|---|---|
| 1    | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2    | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3    | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 4    | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5    | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 6    | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 7    | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8    | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9    | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11   | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 13   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15   | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16   | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19   | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20   | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
The clusters can be analyzed in the graph and the table, mainly focus on A, D, and G classes, the range of their characteristic vector margin index, RMS and pulse index as follows:

| Class | Margin index | RMS     | Pulse index |
|-------|--------------|---------|-------------|
| A     | 1.5795±0.1   | 2.1278±0.1 | 8.6650±1   |
| D     | 1.7915±0.1   | 1.8328±0.2 | 10.3957±1  |
| G     | 2.0625±0.2   | 1.5986±0.1 | 13.1490±2  |

It can be seen from the table that a group of eigenvectors of each state has its own characteristics. Within a month, the quayside container crane hoisting motor is in normal range and does not fail, so this difference of the clustering index value is not big. So, the SOFM algorithm can achieve very accurate state recognition and visualization, which can monitor the mechanical state better. Then it should be paid special attention to the state of this machine, and timely inspect and repair when the eigenvector index difference is too big in the future.

4. Conclusion
The processed data is based on the day as a unit, and then carried out the motor status identification and visualization to achieve a very accurate clustering and visualization by using self-organizing feature map (SOFM) algorithm. The processed data is also based on the hour as a unit to achieve a more accurate analysis. Through the data acquisition and processing of the hoisting motor, it is possible to accurately identify the working state of the motor, thus provide better monitoring of the hoisting bridge motor and ensure the motor normal and stable and avoid the occurrence of some accidents.

Acknowledgements
This work was supported by the National Natural Science Foundation of China (No. 31300783), China Postdoctoral Science Foundation (No. 2014M561458), Doctoral Fund of the Ministry of Education Jointly Funded Project (No. 20123121120004), the Shanghai Maritime University Research Project (No. 20130474), the Shanghai Top Academic Discipline Project- management science & engineering, and the high-tech research and development program of China (No. 2013A2041106).

References
[1] Wang Z X 2008 Data Mining and Condition Recognition on Characteristic Data of Quayside Container D. Shanghai Jiaotong University
[2] Ma Y and Ruan Y 2011 J. Vector Quantization Method Based on Improved SOFM Neural Network J. Journal of Computer Engineering and Science
[3] Yi F Research on Extraction Method of Network Security Situation Elements Based on Evolutionary Neural Network Model J. Electronic world.
[4] Xiao K and Yuan S C 2010 Application of SOM Neural Network in Fault Diagnosis of Rotating Machines J. Mechanical Design and Manufacturing.
[5] Kohonen T 1998 The Self-organizing Map J.Neurocomputing.
[6] Kohonen T 1982 Self-organized formation of topologically correct feature maps D. Biological Cybernetics.
[7] Chen C P 2009 Crane control using machine vision and wand following J.IEEE International.
[8] Zheng Z Y, Chen YY and Zhang J etal. 2013 An Improved Pre-processing Algorithm of Radar Signal Sorting Based on SOFM Clustering J. Aerospace Electronic Warfare
[9] Dai S B, Lei W H and Cheng Y Z etal. 2015 Research on Combined SOFM and SVC Clustering Method for Pre-deinterleaving of Radar Pulse J. Firepower and Command Control.
[10] Ivrissimtzis I P, Jeong W K and Seidel H P, 2003 Using growing cell structures for surface reconstruction. Proceedings of the Shape Modeling International.
[11] Dai S B, Lei W H and Cheng Y Z etal. 2014 Clustering of DOA data in radar pulse base Don SOFM and CDBW J.Journal of Electronics.