Automated Knowledge Acquisition Based On Unsupervised Neural Network & Expert System Paradigms

Nazar Elfadil, Md.Abdus Salam,Zia Nadir
College of Engineering, Sultan Qaboos University
P.O. Box 33, Post Code 123, Muscat, Sultanate of Oman
Tel: +968-9523864, Fax: +968-513454.

Abstract--Self-organizing maps are an unsupervised neural network model that lends itself to the cluster analysis of high dimensional input data. However, interpreting a trained map proves to be difficult because the features responsible for specific cluster assignment are not evident from resulting map representation. Paper presents an approach for automated knowledge acquisition system using Kohonen self-organizing maps and k-means clustering. For the sake of illustrating the system overall architecture and validate it, a data set represent world animal has been used as training data set. The verification of the produced knowledge based had done by using conventional expert system.

Key words: Kohonen self-organizing maps, Machine learning, automated knowledge acquisition.

1. INTRODUCTION

In our daily life, we cannot avoid making decisions. Decision-making may be defined as making a conclusion or determination upon a problem at hand. However, in recent years, problems to be solved have become more complex. Consequently, knowledge based decision-making systems have been developed to aid us in solving complex problems. The demand for automated knowledge acquisition system has increased dramatically.

The previous approaches for automated knowledge acquisition are based on decision trees, progressive rule generation, and supervised neural networks [1]. All the above-mentioned approaches are supervised learning methods, requiring training examples combined with their target output values. In the real world cases, target data is not always known so as to provide to the system before start training the data set[2].

This paper is organized as follows: Section 2 presents an overview of the automated knowledge acquisition. Section 3 demonstrates illustrative application. Finally section 4 illustrates the conclusion and future work..

2. AUTOMATED KNOWLEDGE ACQUISITION

The paper proposes an automated knowledge acquisition method in which, knowledge (connectionist) is extracted from data that have been classified by a Kohonen self-organizing map (KSOM) neural network. This knowledge (at this stage) is of the intermediate-level concept rule hierarchy. The final concept rule hierarchy is generated by applying a rule generation algorithm that is aided by an expert system inference engine. The resulting knowledge (symbolic) may be used in the construction of the symbolic knowledge base of an expert system. The proposal is rationalized from the realization that most complex real-world problems are not solvable using just symbolic or just adaptive processing alone [3]. As depicted in Figure 2, the methodology of the proposed system consists of four main phases namely, data preprocessing, KSOM learning and k-means clustering, symbolic rule extraction and formation of knowledge base.

3. ILLUSTRATIVE APPLICATION

The identification of possible faulty condition in the machine from data patterns can enhance the ability to act proactively and more efficiently so as to maximize productivity and eliminating unplanned downtime. Automation of this process depends critically on the existence of electrical signatures that can be acquired from the machine; and these signatures should uniquely correspond to specific condition of the machine.

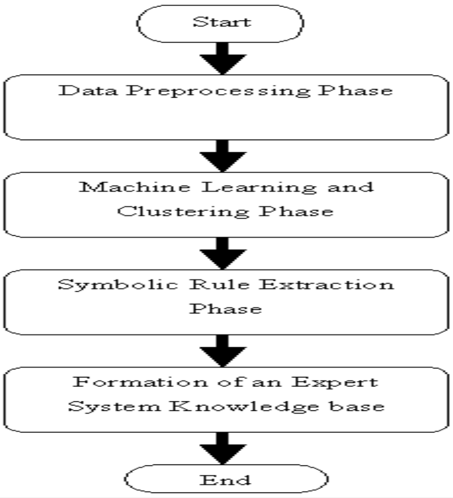

Figure 2: The functional block diagram of knowledge acquisition system

3.1 Background of the Problem

The functional block diagram of this problem consists of three main models; namely: wire bonding machine and data acquisition, feature extraction, and knowledge acquisition and condition recognition. This is shown in Figure 3.

The wire-bonding machine that is used in this case study is the ABACUS III wire-bonding machine found in semiconductor manufacturing plant. The wire bonding process is third process in the assembly and test of integrated circuits and it is the most commonly employed interconnection technique in the semiconductor industry. Its objective is to attach very fine gold wires from the silicon die (sawn chips from wafers) to the lead frame. This interconnection offers a low resistance for the electrical signal to be propagated functionally and completely.

The data collected from the machine is a signature signal that corresponds to the operating condition of the machine. The shape of the signature reflects the condition of the machine. Any distortion or abnormalities in the shape of the signal compared to that of a normal signature indicates a problem, and corrective measures can then be taken to avoid producing further rejects and also unplanned breakdown of the machine.

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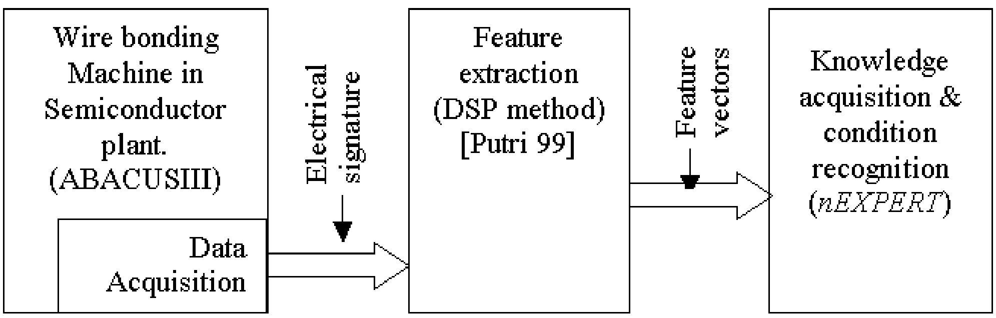


Figure 3: Functional block diagram of condition monitoring problem

In this case study the electrical signature is the damping signal of the bond head subassembly of the wire-bonding machine. The damping signatures are collected by connecting a digital oscilloscope with storage capacity to a predetermined test point on the bond head driver (galvo) card of the wire-bonding machine. These form the data acquisition module in the functional block diagram above.

The damping signature of the bond head subassembly can be described by the following continuous time equation [x]:

$$\left.\begin{aligned} x(t) &= A \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . t_0 < t < t_1 \\ x(t) &= -0.0625 \; A \exp\left(-\frac{t-t_1}{\tau_0}\right) \ldots\ldots\ldots\ldots\ldots t_1 < t < t_2 \\ x(t) &= -A \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots t_2 < t < t_3 \\ x(t) &= A\left[-1+\left[1-\exp\left(-\frac{t-t_3}{\tau_1}\right)\right]\right]\cos(2.\pi.f_1 t)\ldots t3 < t < t_4 \end{aligned}\right\} \quad (1)$$

Where A is a constant, f_0 and f_1 are the frequencies, and τ_0 and τ_1 are the time constants for the signal. A damping signature can be divided into three parts namely: the fall signal, the rise signal and the steady state part. The fall signal and the rise signal refer to part of the signal from $t_1 < n < \frac{(t_1+t_2)}{2}$ and $t_3 < n < \frac{(t_3+t_4)}{2} t$ respectively. Interval from $\frac{(t_1+t_2)}{2} < t < t_2$ and $\frac{(t_3+t_4)}{2} < t < t_4$ is the steady state signal. Figure 4 shows an example of the damping signature of a good condition machine.

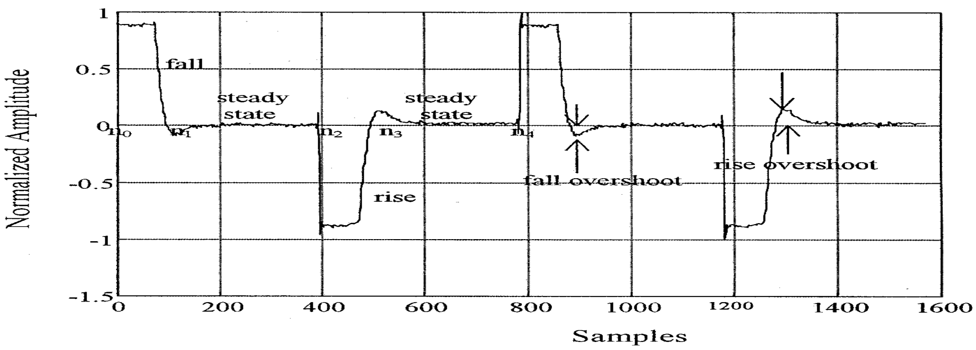


Figure 4: Good damping signature

Any problem that is encountered by the machine will result in a deviation in the damping signature from that defined in Equation 1 above. This is characterized by the values of frequencies and time constants that deviate from the system specifications. The extraction of unique feature vectors from the collected signatures requires further analysis.

In terms of signals, correlation between two signals or between one part of a signal to another part of the same signal is to measure the degree to which they are similar and thus extract the information present in it. Specifically, the cross-correlation function and autocorrelation function are used for this purpose. In this case study the autocorrelation is used. The autocorrelation function is defined as the measure of dependence of successive samples *x(n-m)* on the previous ones *x(n)* and is carried out by:

$$R_{xx}(m) = \sum_{n=0}^{N-|m|-1} x(n)x(n-m) \quad (2)$$

Where N is the total number of samples and time lag $m = \pm (0,1 \ldots N-1)$

The rise time autocorrelation function is evaluated during the interval $n_3<n<n_4$ as shown in Figure 2. The fall time autocorrelation function is evaluated during the interval $n_1<n<n_2$. Figure 5 shows the distribution of parameters for fall time autocorrelation and rise time autocorrelation.

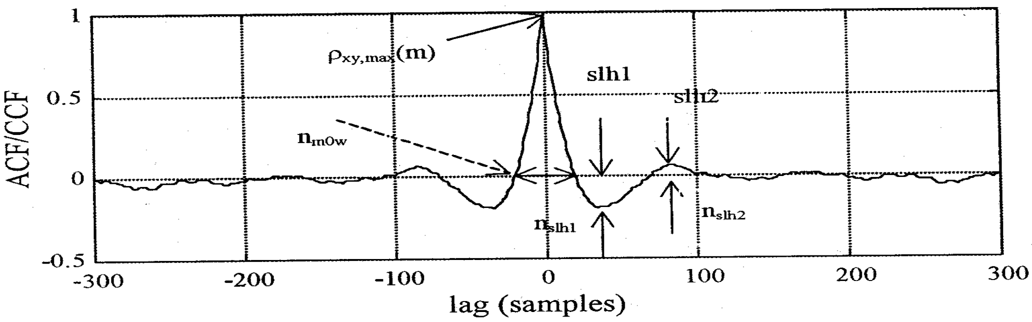
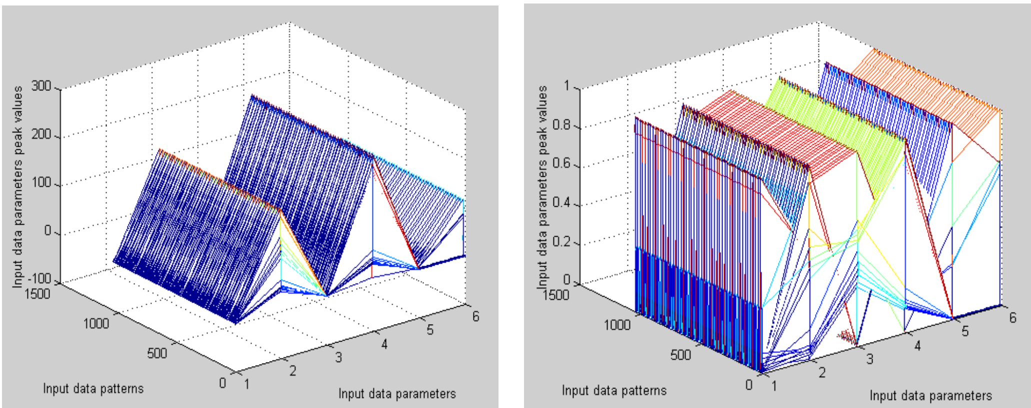


Figure 5: Distribution of parameters for the RTAC and FTAC [x]

3.2 Rise-Time Auto-Correlation (RTAC) Case Study

This data set is derived from [x]. The goal of *nEXPERT* is to predict the current machine condition given the feature vectors. The data set is composed of 1300 input feature vectors (examples). Each of which is associated with a machine condition feature. Each input vector consist of six RTAC signal function parameters. Figure 6 shows the input data before and after normalization. Normalization removes dominance among the input feature vectors parameters, as shown in Figure 4 (b). The Kohonen NN learning and modified K-means clustering outputs are illustrated in Figure 5 and Figure 6, respectively. Eight clusters are obtained.



(a) Before (b) After

Figure 6: Input data before and after normalization (RTAC)

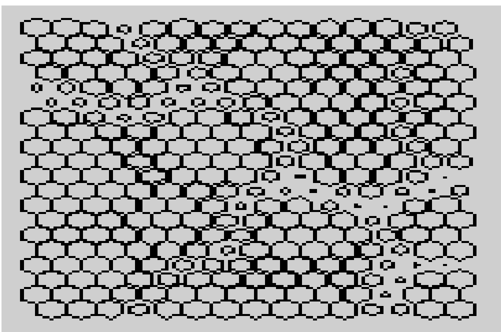


Figure 7: Kohonen NN learning & clustering session output (RTAC)

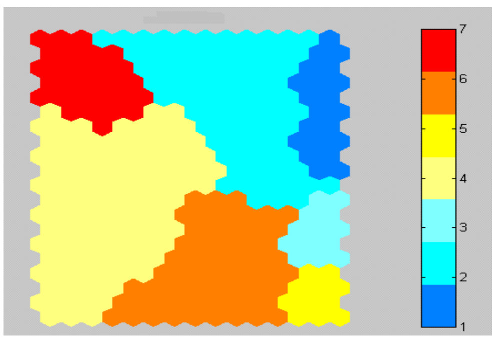


Figure 8: Modified K-means clustering session output (RTAC)

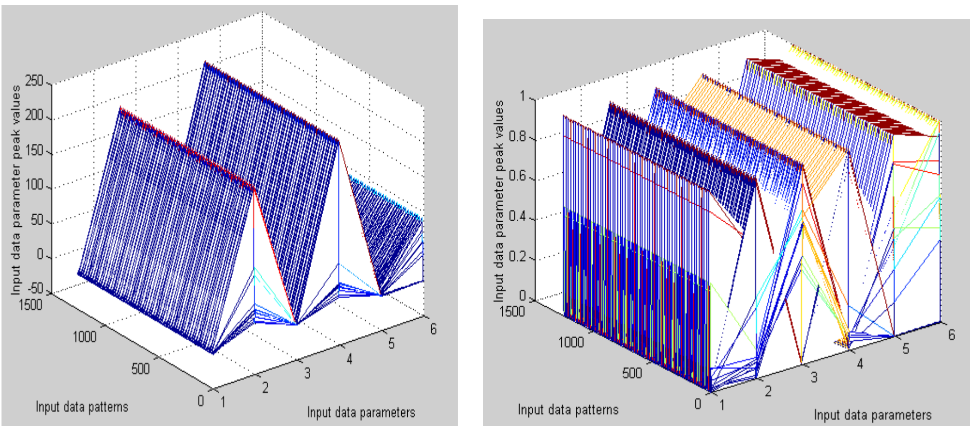
By using Boolean algebra in removing symbolic redundancy among the extracted rules that represent same cluster, the contents of Table 2 is updated to new comprehensive set with less number of rules; as shown in Table 3. In other words, for example rules 1.1, 1.2, and 1.3 that indicate by rule number 1 in Table 2 could be reduced to only two rules; as shown by rule number 1 in Table 3. This removal of symbolic redundancies in the antecedents, followed by the knowledge base formation phase of *nEXPERT* results in the formation of the symbolic rule base shown in Table 3.

Table 2: Antecedents – to – cluster mapping (RTAC)

Rule No.	Antecedents part	Cluster index
1	1.1 (Rise shift= low)& (n_{mow} = high)& (s1h1= high)& (n_{s1h2}= low)& (s1h2= high)& (ns1h2= high) 1.2 (Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (n_{s1h2}= low)& (s1h2= high)& (ns1h2= high) 1.3 (Rise shift= low)& (n_{mow} = low)& (s1h1= low)& (ns1h2= low)& (s1h2= low)& (ns1h2= high) 1.4 (Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (ns1h2= low)& (s1h2= low)& (ns1h2= high	Cluster 1
2	(Rise shift= low)& (n_{mow} = low)& (s1h1= low)& (n_{s1h2}= low)& (s1h2= high)& (ns1h2= high)	Cluster 2
3	(Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (ns1h2= high)& (s1h2= low)& (ns1h2= low)	Cluster 4
4	4.1 (Rise shift= low)& (n_{mow} = high)& (s1h1= high)& (ns1h2= high)& (s1h2= low)& (ns1h2= low). 4.2 (Rise shift= low)& (n_{mow} = high)& (s1h1= low)& (ns1h2= high)& (s1h2= low)& (ns1h2= low).	Cluster 5
5	5.1 (Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (ns1h2= low)& (s1h2= low)& (ns1h2= low) 5.2 (Rise shift= high)& (n_{mow} = low)& (s1h1= low)& (ns1h2= low)& (s1h2= low)& (ns1h2= low) 5.3 (Rise shift= high)& (n_{mow} = high)& (s1h1= low)& (ns1h2= low)& (s1h2= low)& (ns1h2= low)	Cluster 6
6	(Rise shift= high)& (n_{mow} = high)& (s1h1= low)& (ns1h2= high)& (s1h2= low)& (ns1h2= low)	Cluster 7
7	(Rise shift= low)& (n_{mow} = low)& (s1h1= low)& (ns1h2= low)& (s1h2= low)& (ns1h2= low)	Cluster 8

Table 3: Extracted symbolic rule base (RTAC)

Rule No.	Antecedents part	Condition
1	1.1 (Rise shift= low)& (s1h1= high)& (n_{s1h2}= low)& (s1h2= high)& (n_{s1h2}= high) 1.2 (Rise shift= low)& (n_{mow} = low)& (n_{s1h2}= low)& (s1h2= low)& (n_{s1h2}= high)	Bad: loose flex pivot
2	(Rise shift= low)& (n_{mow} = low)& (s1h1= low)& (n_{s1h2}= low)& (s1h2= high)& (n_{s1h2}= high)	Bad: loose linkage bearing (minimal)
3	(Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (n_{s1h2}= high)& (s1h2= low)& (n_{s1h2}= low)	Bad: spring at the back of the wire pressed
4	(Rise shift= low)& (n_{mow} = high)& (n_{s1h2}= high)& (s1h2= low)& (n_{s1h2}= low).	Bad: board problem
5	5.1 (Rise shift= low)& (n_{mow} = low)& (s1h1= high)& (n_{s1h2}= low)& (s1h2= low)& (ns1h2= low) 5.2 (Rise shift= high)& (s1h1= low)& (n_{s1h2}= low)& (s1h2= low)& (n_{s1h2}= low)	Bad: loose galvo linkage screw
6	(Rise shift= high)& (n_{mow} = high)& (s1h1= low)& (n_{s1h2}= high)& (s1h2= low)& (n_{s1h2}= low)	Bad: Bent scanner
7	(Rise shift= low)& (n_{mow} = low)& (s1h1= low)& (n_{s1h2}= low)& (s1h2= low)& (n_{s1h2}= low)	Good



(a) Before **(b) After**

Figure 9: Input data before and after normalization (FTAC)

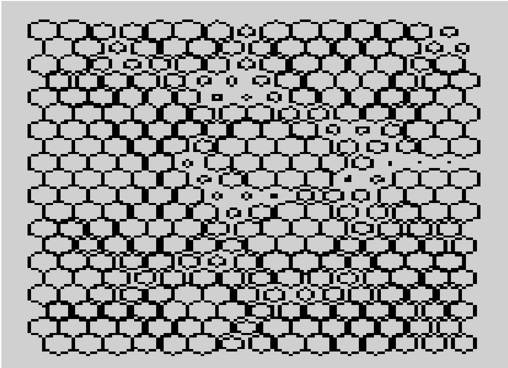


Figure 10: Kohonen NN learning output (FTAC)

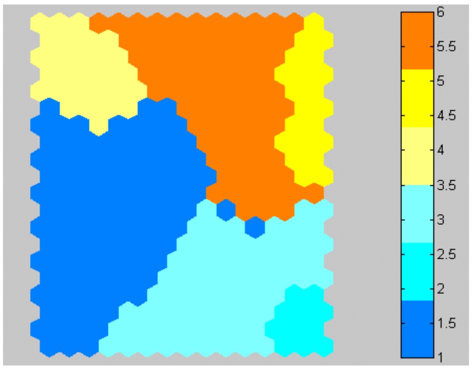


Figure 11: Modified K-means clustering output ((FTAC)

3.3 Fall-Time Auto-Correlation (FTAC) Case Study

The data set composed of 1260 input feature vectors (examples). Each input vector consist of 6 *FTAC* function parameters, as indicated in Table 6 below.

Figure 9 (a) and (b) show input data before and after normalization process. Figure 10 and Figure 11 illustrate the output of Kohonen NN learning session, and modified K-means clustering session, respectively. *nEXPERT* system clusters the input data into various clusters that represent Good and Bad signals. *nEXPERT* system provides 13 symbolic rules that represent the various extracted knowledge.

4 Conclusion

Condition-monitoring case studies show that the proposed *nEXPERT* system successfully extracted knowledge in the form of production rules from numerical data set representing the salient features of the problem domain. This study has demonstrated that symbolic knowledge extraction can be performed using unsupervised learning Kohonen NN neural networks, where no target output vectors are available during training. The system is able to learn from examples via the neural network section. The extracted knowledge can form the knowledge base of an expert system, from which explanations may be provided, and it is quite possible to diagnose new unknown feature. Large, noisy and incomplete data set can be handled. The system proves the case of the viability of integrating neural network and expert system to solve real-world problems.

Despite FTAC and RTAC are different approaches, but the same signature yields the same diagnosis.The difference between both approaches is that; RTAC produced 7 clusters with 9 symbolic rules (knowledge base) while FTAC managed to produce 7 clusters with 12 symbolic rules. Obviously the approach that produced cluster with less number and comprehensible rules is considered a superior. In other words, RTAC show some superiority over the FTAC in this case study.

5 References

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