ARTICLE IN PRESS
JID: NEUCOM [m5G;April 6, 2017;14:20]
Neurocomputing 000 (2017) 1–7
Contents lists available at ScienceDirect
Neurocomputing
journal homepage: www.elsevier.com/locate/neucom

Application of self-organizing map to failure modes and effects analysis methodology

Wui Lee Chang, Lie Meng Pang, Kai Meng Tay*

Faculty of Engineering, Universiti Malaysia Sarawak, Sarawak, Malaysia

ARTICLE INFO

Article history:
Received 23 September 2015
Revised 3 December 2015
Accepted 10 April 2016
Available online xxx

Keywords:
Failure modes and effects analysis
Clustering
Visualization
Self-organizing map
Risk Priority Number Interval

ABSTRACT

In this paper, a self-organizing map (SOM) neural network is used to visualize corrective actions of failure modes and effects analysis (FMEA). SOM is a popular unsupervised neural network model that aims to produce a low-dimensional map (typically a two-dimensional map) for visualizing high-dimensional data. With regards to FMEA, it is a popular methodology to identify potential failure modes for a product or a process, to assess the risk associated with those failure modes, also, to identify and carry out corrective actions to address the most serious concerns. Despite the popularity of FMEA in a wide range of industries, two well-known shortcomings are the complexity of the FMEA worksheet and its intricacy of use. To the best of our knowledge, the use of computation techniques for solving the aforementioned shortcomings is limited. The use of SOM in FMEA is new. In this paper, corrective actions in FMEA are described in their severity, occurrence and detect scores. SOM is then used as a visualization aid for FMEA users to see the relationship among corrective actions via a map. Color information from the SOM map is then included to the FMEA worksheet for better visualization. In addition, a Risk Priority Number Interval is used to allow corrective actions to be evaluated and ordered in groups. Such approach provides a quick and easily understandable framework to elucidate important information from a complex FMEA worksheet; therefore facilitating the decision-making tasks by FMEA users. The significance of this study is two-fold, viz., the use of SOM as an effective neural network learning paradigm to facilitate FMEA implementations, and the use of a computational visualization approach to tackle the two well-known shortcomings of FMEA.

1. Introduction

Failure modes and effects analysis (FMEA) is an effective problem prevention and risk analysis methodology for defining, identifying, and eliminating failures of a system, design, process, or service [1]. A search in the literature reveals that FMEA was extensively used in a wide range of application domains, e.g., aerospace [2], automotive [1], nuclear [3], electronic [4], manufacturing [5,6], chemical [7], mechanical [8], healthcare and hospital [9], and agriculture [10]. FMEA usually starts with identifying the failure modes of a system or process, understanding the causes and effects of each failure mode, and determining suitable corrective actions to eliminate or reduce the risk of the respective failure modes [1]. Traditionally, the risk of a failure mode is determined by a Risk Priority Number (RPN) model [1]. The RPN model considers three risk factors as its inputs, i.e. severity (S), occurrence (O), and detection (D), and produces an *RPN* score (i.e. multiplication of S, O, and D) as the output [1]. S and O are seriousness and frequency of a failure mode and its root cause(s), respectively, while D is the effectiveness of the existing measures in detecting a failure mode before the effect of the failure mode reaches the customer(s) [1].

While the effectiveness of FMEA has been demonstrated, three shortcomings pertaining to practical implementation of FMEA are as follows. (1) its risk evaluation and prioritization issues [2,5,11,12]; (2) the complexity of the FMEA worksheet [13]; and (3) its intricacy of use [13,14]. The first shortcoming is well known and much research works have been conducted [2,11]. The first shortcoming suggests that the traditional RPN model is susceptible to a number of limitations, among the popular are, (1) relative importance among S, O and D is not taken into consideration [2], (2) different combinations of S, O and D may produce exactly the same value of RPN, but their hidden risk implications may be totally different [5], (3) the three risk factors are difficult to be precisely evaluated [11], (4) the mathematical formula for calculating RPN is questionable [11] and etc. Besides, according to a review from [11], the existing risk evaluation methods can be grouped into five categories, i.e., multi-criteria decision making methods, mathematical programming methods, artificial intelligence methods, integrated methods, and other methods.

* Corresponding author.
E-mail addresses: kmtay@unimas.my, tkaimeng@yahoo.com (K.M. Tay).

http://dx.doi.org/10.1016/j.neucom.2016.04.073
0925-2312/

Even though much works on the first shortcoming has been reported, to the best of our knowledge, little effort was on the other two shortcomings. The second shortcoming suggests that FMEA worksheet is complex [13]. Entries in a FMEA worksheet are voluminous [13]. An example of an FMEA table (e.g. see [1], pages 231–242) could take up to 11 pages. The third shortcoming suggests that the FMEA worksheet is hard to produce [13,14], hard to understand and read, as well as hard to maintain [13,14]. It was reported that FMEA, as implemented in Microsoft Excel, is unwieldy with much mouse scrolling required [13]. Too much mouse scrolling detracts FMEA users' mental representation of the FMEA worksheet as a whole, and prevents FMEA users from seeing the overall structure of the FMEA worksheet [13]. Failure analysis matrix (FAM) worksheet, a much smaller worksheet that requires less mouse scrolling, was then proposed as a finder and gentler alternative to, but not as a total replacement for, FMEA worksheet [13]. Other efforts to computerize or automate design FMEA were also reported [14-16]. However, it is not clear how these works [14-16] could be applied to process FMEA, or FMEA in general.

The main aim of this paper is to examine the use of the self-organizing map (SOM) neural network for analyzing (i.e., both clustering and visualization) failure modes and corrective actions in FMEA. The focus of this paper is on clustering and visualization of corrective actions. Fuzzy adaptive resonance theory (ART) was firstly used by Keskin and Özkan [17] to tackle the problem whereby different combinations of S, O, and D could produce the same *RPN* scores. In addition to this reason, we further justified the advantages of using clustering and visualization methods in FMEA, as follows: (1) clustering and visualization deals with the original S, O, and D scores directly [18]; (2) clustering and visualization allows the failure modes to be compared and visualized in the input space as groups of information [18]; (3) the use of the original S, O, and D scores (instead of the mapped S, O, and D scores into a common domain) avoids loss of information or modification of important information for decision making purposes [18].

In our previous work [19], clustering and visualization methods were suggested as a solution for tackling the two above-mentioned shortcomings related to FMEA implementation, i.e., the complexity of the FMEA worksheet and its intricacy of use. From our literature research, limited investigations on using computing techniques to solve the aforementioned issues have been reported so far. Visualization serves as a communication means between FMEA worksheet and its users [19]. A good visualization (or effective communication) is important because (1) it presents the corrective actions as a structure that is easy to understand, as compared with the original corrective actions in complex FMEA worksheets [19]; (2) it allows users to access or analyze FMEA with a large number of corrective actions quickly, which may not be otherwise possible [19]; (3) it provides users an overview of all corrective actions, which mitigates the problem in having a good understanding and insight into the overall FMEA exercise in situations where no visualization is available [19]; and (4) it leads to more efficient processes for making decisions and taking actions [19].

In our previous work, two incremental-learning neural network models (i.e., fuzzy ART [20] and evolving tree [21]) were used for analysis of failure modes in FMEA. In [18], fuzzy ART was used to cluster failure modes to groups based on their similarity, in which failure modes within a cluster share higher similarity measures, as compared to those associated with other clusters. In [19], evolving tree was used for analyzing (i.e., both clustering and visualization) failure modes in a complicated FMEA worksheet, instead of just performing clustering only as in the use of fuzzy ART [18]. Failure modes were transformed to a tree structure for better visualization [19]. Such visualization is useful as it provides a quick and easily understandable representation of the FMEA worksheet, which is usually complex and lengthy, to facilitate decision making tasks. Two concepts, i.e., risk interval and risk ordering of clusters, were introduced to allow failure modes or corrective actions to be analyzed in a group [18,19].

Instead of fuzzy ART and evolving tree, SOM is used for both clustering and visualization of corrective actions in FMEA, in this paper. To the best of our knowledge, the use of SOM in FMEA is new. SOM is a neural network capable of mapping high dimensional data samples onto a lower dimensional space and representing them as nodes [22-24]. It also provides a topological view of the underlying data structure [22-24]. In this paper, SOM is used as a visualization aid for FMEA users to see the relationship among corrective actions via a color map. Color information from the SOM map is then included to the FMEA worksheet for better visualization. SOM is chosen because of its topological preserving feature [23]. However, a drawback of using SOM is that map size has to be predefined and this may lead to experiments with different sized maps, trying to obtain the optimal result [21]. In addition, the proposed risk interval and risk ordering equations for different groups of failure modes from [18] are used to allow corrective actions to be ordered and evaluated in groups. To evaluate the proposed method, benchmark information from [1] (pages 231–242) is used. The experimental results show that the complicated and lengthy FMEA worksheets can be clustered and visualized as a comprehensible SOM map with color. Inclusion of color information from the SOM map to the FMEA worksheet could provide FMEA users a good understanding and insight of corrective actions.

This paper is organized as follows. In Section 2, the background of FMEA and the RPN model is explained. In Section 3, the use of SOM in FMEA is described. In Section 4, the experimental results are presented and discussed. Finally, concluding remarks are provided in Section 5.

2. Preliminaries

To make this paper self-contained, the RPN model is explained and discussed.

2.1. Severity, occurrence, detection and Risk Priority Number

Traditionally, FMEA adopts an RPN model, which considers three risk factors, i.e., S, O, and D, for prioritizing the corrective actions. These three risk factors are defined as follows.

Definition 1. A risk factor, $X \in [S, O, D]$, is considered. Variables s, o, and d are the elements of S, O, and D, respectively, i.e., $s \in$ S, $o \in$ O, and $d \in D$. The lower and upper boundaries of S are represented by $\underline{s}$ and $\bar{s}$, respectively. Similarly, the lower and upper boundaries of O and D are represented by $\underline{o}$ and $\bar{o}$, as well as $\underline{d}$ and $\bar{d}$, respectively. In this paper, an $S \times O \times D$ bounded space, which is a combination of S, O, and D risk factors, is further considered.

An RPN model produces an *RPN* score. The space containing all *RPN* scores is defined as follows.

Definition 2. The *RPN* space is the output space containing all possible *RPN* scores. The lower and upper boundaries of the RPN space are represented by $\underline{RPN}$ and $\overline{RPN}$, respectively. Ideally, the *RPN* space follows a monotonic, ordered sequence, i.e., the higher the *RPN* score, the higher the risk.

The aim of the traditional FMEA is to prioritize corrective actions. A corrective action in FMEA is described in their S, O and D scores, i.e., $[s, o, d]$. A set of corrective actions as defined in Definition 3 is considered.

Definition 3. m corrective actions, described as $\overline{x_k} = [s_k \in \mathrm{S}, o_k \in \mathrm{O}, d_k \in \mathrm{D}]$, $k = 1, 2, 3, \ldots, m$, is considered.