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Clustering and visualization of failure modes using an evolving tree

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ABSTRACT

Despite the popularity of Failure Mode and Effect Analysis (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. As such, the idea of clustering and visualization pertaining to the failure modes in FMEA is proposed in this paper. A neural network visualization model with an incremental learning feature, i.e., the evolving tree (ETree), is adopted to allow the failure modes in FMEA to be clustered and visualized as a tree structure. In addition, the ideas of risk interval and risk ordering for different groups of failure modes are proposed to allow the failure modes to be ordered, analyzed, and evaluated in groups. The main advantages of the proposed method lie in its ability to transform failure modes in a complex FMEA worksheet to a tree structure for better visualization, while maintaining the risk evaluation and ordering features. It can be applied to the conventional FMEA methodology without requiring additional information or data. A real world case study in the edible bird nest industry in Sarawak (Borneo Island) is used to evaluate the usefulness of the proposed method. The experiments show that the failure modes in FMEA can be effectively visualized through the tree structure. A discussion with FMEA users engaged in the case study indicates that such visualization is helpful in comprehending and analyzing the respective failure modes, as compared with those in an FMEA table. The resulting tree structure, together with risk interval and risk ordering, provides a quick and easily understandable framework to elucidate important information from complex FMEA forms; therefore facilitating the decision-making tasks by FMEA users. The significance of this study is twofold, *viz*., the use of a computational visualization approach to tackling two well-known shortcomings of FMEA; and the use of ETree as an effective neural network learning paradigm to facilitate FMEA implementations. These findings aim to spearhead the potential adoption of FMEA as a useful and usable risk evaluation and management tool by the wider community.

1. Introduction

Clustering is a process of organizing a set of data attributed by multi-dimensional features into different groups based on a similarity measure (Rui & Donald, 2009). Usually, each group of data is represented by a unique weight vector, e.g. the centroid of the group (Rui & Donald, 2009). Clustering methods are useful in many applications, e.g. data mining (Lan, Frank, & Hall, 2005), data query (Lan et al., 2005), robotic arm movements (Kohonen, Simula, & Visa, 1996), noise reduction in telecommunication (Kohonen, 2001), and image segmentation (Chang, Luo, & Parker, 1998). Examples of popular clustering methods include the self-organizing map (SOM) (Vesanto & Alhoniemi, 2000), the evolving tree (ETree) (Pakkanen, Iivarinen, & Oja, 2006), fuzzy ART (Keskin & Özkan, 2009), as well as k-means (Chang et al., 1998) and fuzzy c-means (Rezaee, Leliveldt, & Reiber, 1998) clustering algorithms.

The SOM model is a neural network capable of mapping high dimensional data samples onto a lower dimensional space and representing them as nodes (Kohonen et al., 1996; Kohonen, 2001; Vesanto & Alhoniemi, 2000). It also provides a topological view of the underlying data structure (Kohonen et al., 1996; Kohonen, 2001; Vesanto & Alhoniemi, 2000). A number of enhanced SOM models have been proposed, e.g. growing SOM (GSOM) (Matharage, Alahakoon, Rajapakse, & Pin, 2011; Kuo, Wang, & Chen, 2012), growing hierarchical SOM (GHSOM) (Huang & Tsaih, 2012), and ETree (Pakkanen, Iivarinen, & Oja, 2004, 2006). These enhancements overcome two shortcomings of SOM, i.e., the requirement of a pre-defined map size before learning (Kohonen, 2001; Vesanto & Alhoniemi, 2000) and the long learning time when a large map size is initiated (Pakkanen et al., 2004, 2006). GSOM starts with a small map, and nodes are added during the

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