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# Rolling bearing fault detection using continuous deep belief network with locally linear embedding

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ABSTRACT

Rolling bearing fault detection is of crucial significance to enhance the availability, the reliability and the security of rotating machinery. In this paper, a novel method called continuous deep belief network with locally linear embedding is proposed for rolling bearing fault detection. Firstly, a new comprehensive feature index is defined based on locally linear embedding to quantify rolling bearing performance degradation. Secondly, a continuous deep belief network (CDBN) is constructed based on a series of trained continuous restricted Boltzmann machines (CRBMs) to model vibration signals. Finally, the key parameters of the continuous deep belief network are optimized with genetic algorithm (GA) to adapt to the signal characteristics. The proposed method is applied to analyze the experimental bearing signals. The results demonstrate that the proposed method is more superior in stability and accuracy to the traditional methods.



## 1. Introduction

Rolling bearing is one of the most important components in rotating machinery of modern industry. Effective rolling bearing fault detection techniques are critically needed to avoid breakdowns of rotating machinery which may result in economical loss and catastrophic accidents [1–3].

Early fault detection or fault prognosis is the focus in Prognostics and Health Management (PHM) [4]. Unlike many methods available for fault diagnosis [5–8], prognosis is still in its infancy. Current fault prognosis models can be classified into three main categories: physical model, knowledge-based model and data-driven model [9]. Physical models are used to describe the various working conditions of the system based on differential equations. Janjarasjitt et al. [10] used a nonlinear dynamical model for rolling bearing condition detection. Lei et al. [11] constructed phenomenological models of vibration signals for epicyclic gearboxes condition monitoring. The limitations of physical models are their high costs and poor generalization ability [9]. Moreover, it is too difficult to build accurate physical model for complex industrial equipment [12]. Expert System and Fuzzy Inference System are currently two popular knowledge-based methods [13]. Hussain et al. [14] developed an expert system for acoustic diagnosis of power circuit breakers and on-load tap changers. Raj et al. [15] combined fuzzy inference and morphological operators for bearing early faults detection. However, it is a great challenge to obtain domain knowledge and convert it to rules exactly [16]. Data-driven models are based on statistical learning theories, and they can capture the useful information hidden in the collected data [17]. Currently, the most popular data-driven models are artificial neural network (ANN) and support vector machine (SVM). Abaei et al. [18] applied self-organizing map neural network for software fault prediction. Barad et al. [19] employed neural network for health monitoring of a gas turbine engine. Selak et al. [20] used SVM for the condition monitoring and fault detection of hydropower plants. Chen et al. [21] proposed SVM for predicting failures of turbines in a thermal power plant. Though the two kinds of data-driven models have been widely used for fault detection, they still have some inherent disadvantages [22,23]. More importantly, SVM and ANN are considered to have shallow architectures, which is, with no more than one hidden layer [24]. Several results have clearly shown that, with an inadequate depth of layers, shallow architectures are difficult to effectively learn the highly non-linear relationships [25–27]. Usually, the development of rolling bearing fault will be a nonlinear and non-stationary time series due to the varying operating conditions [28,29]. What's worse, in the early stages of bearing failures, the fault information is often overwhelmed by

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heavy noises. In these cases, it is a great challenge to adopt shallow architectures to perform accurate fault detection. Thus, it is necessary to construct deep architectures for learning the complex non-linear relationships in machinery fault detection issues.

In 2006, a great breakthrough in deep learning was initiated by Hinton and quickly followed up later [30]. Generally, deep learning models have two attractive advantages. Firstly, they should also belong to the scope of neural networks with great abilities of learning and nonlinear mapping. Secondly, multiple nonlinear hidden layers make them more likely to effectively and flexibly express any highly varying non-linear functions than shallow learning models [31,32]. Deep belief network (DBN) is one of the most popular deep learning methods, which has been gradually applied in machinery fault diagnosis in the last three years [33–35]. However, DBN is still in its infancy in machinery fault prognosis. Therefore, it is very meaningful to construct novel DBN model for early fault detection of machinery.

In this paper, a novel method called continuous deep belief network (CDBN) with locally linear embedding is proposed for bearing fault detection. The proposed method is applied to analyze the experimental bearing signals. The results show that the proposed method is more effective than the existing methods. The main contributions of our work can be summarized as follows.

1) In order to accurately quantify rolling bearing performance degradation, locally linear embedding algorithm is used to define a new comprehensive feature index.
2) In order to effectively learn the highly non-linear relationships hidden in the measured vibration signals, a continuous deep belief network is constructed based on a series of trained continuous restricted Boltzmann machines to model vibration signals.
3) In order to enable the continuous deep belief network adapt to the signal characteristics, genetic algorithm is adopted to optimize its parameters.

The remainder of this paper is organized as follows. In Section 2, the deep belief network theory is given briefly. The proposed method is introduced in Section 3. In Section 4, the experimental results of the proposed method are shown. Finally, the conclusions and future works are given in Section 5.

## 2. Deep belief network theory

DBN is a deep neural network consists of several restricted Boltzmann machines (RBMs). As shown in Fig. 1(**a**), the visible layer $\mathbf{v}$ and the first hidden layer $\mathbf{h^1}$ constitutes the first RBM (RBM 1), the first hidden layer $\mathbf{h^1}$ and the second hidden layer $\mathbf{h^2}$ constitutes the second RBM (RBM 2), and the second hidden layer $\mathbf{h^2}$ and the third hidden layer $\mathbf{h^3}$ constitutes the third RBM (RBM 3). $\mathbf{W}^j$ denotes the connection weight matrix between layer $j$-1 and layer $j$.

As shown in Fig. 1(**b**), $\mathbf{v} = (v_1, v_2, \cdots, v_n)$ denotes the state of the visible units, and $\mathbf{h} = (h_1, h_2, \cdots, h_m)$ the state of the hidden units. The conditional probability distributions of different units can be calculated as [30]

$$P(v_i = 1|\mathbf{h}) = \frac{1}{1 + \exp(-\sum_{j=1}^{m} w_{ij}h_j)} \tag{1}$$

$$P(h_j = 1|\mathbf{v}) = \frac{1}{1 + \exp(-\sum_{i=1}^{n} v_i w_{ij})} \tag{2}$$

where $v_i$ and $h_j$ represent the states of the *ith* visible unit and *jth* hidden unit, respectively. $w_{ij} = w_{ji}$ is the weight between the *ith* visible unit and *jth* hidden unit.

In RBM training process, the Minimizing Contrastive Divergence (MCD) training rule for an RBM replaces the computationally expensive relaxation search of the Boltzmann Machine with a single step of Gibbs sampling [36]. In each iteration, the weight $w_{ij}$ can be updated based on the MCD rule as follows

$$\Delta w_{ij} = \eta(< v_i h_j > - < v'_i h'_j >) \tag{3}$$

where $\eta \in (0, 1)$ is a learning rate, $<\cdot>$ refers to the expectation over the training data. $v'_i$ and $h'_j$ are the reconstructed states of $v_i$ and $h_j$, respectively.

## 3. The proposed approach

In this paper, we propose a novel method called continuous deep belief network with locally linear embedding for rolling bearing fault detection. This method includes four parts, comprehensive feature index definition, continuous deep belief network

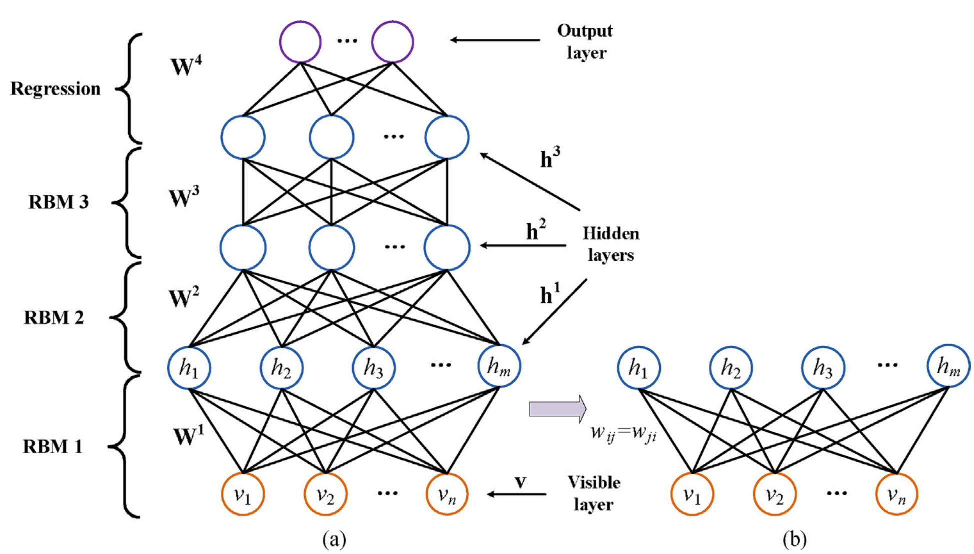


**Fig. 1.** Deep belief network and restricted Boltzmann machine: (a) A DBN with three hidden layers; (b) An RBM with $n$ visible units and $m$ hidden units.