# Big vibration data identification of bearing fault base on autoencoder network-based feature representation and optimal LSSVM-PSO classifier model

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# Abstract

In this paper, based on deep learning method for the high-dimensional feature representation of vibration signal and optimal machine learning model, a new diagnosis technique for multi-level fault of roller bearing is proposed. Firstly, a deep learning network based on stacked autoencoders (SAE) with two hidden layers is exploited for vibration feature extraction (VFE) of roller bearing fault signal, named as VFE-SAE, in which the unsupervised learning algorithm is used to reveal the significant properties in the data such as nonlinear, non-station properties. The extracted features can provide good discriminability for fault diagnosis task. Secondly, an optimal classifier model based on least square support vector machine (LSSVM) classifier and particle swarm optimization (PSO), named as LSSVM-PSO, is used to perform supervised fine-turning and classification. In which, the classifier model is trained with the labeled features to identify the target data. Especially, in this work by the transfer learning the performance of bearing fault diagnosis technique can be tuned. That is, the features of target vibration signal can be extracted by the learning of feature representation which depends on the weight matrix of hidden layers of VFE-SAE method. The experimental results by analyzing the roller bearing vibration signals with multi-status of fault have demonstrated that the VFE-SAE based feature extraction in conjunction with the LSSVM-PSO classifier model can achieve higher accuracies than the other popular classifier models.

**Keyword:** Vibration Feature Extraction; Deep Learning Network; Stacked Autoencoder; Transfer Learning; Multi-level Fault; LSSVM-PSO classifier model.

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