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Vibration and acoustic frequency spectra for industrial process modeling using selective fusion multi-condition samples and multi-source features

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ABSTRACT

Frequency spectral data of mechanical vibration and acoustic signals relate to difficult-to-measure production quality and quantity parameters of complex industrial processes. A selective ensemble (SEN) algorithm can be used to build a soft sensor model of these process parameters by fusing valued information selectively from different perspectives. However, a combination of several optimized ensemble sub-models with SEN cannot guarantee the best prediction model. In this study, we use several techniques to construct mechanical vibration and acoustic frequency spectra of a data-driven industrial process parameter model based on selective fusion multi-condition samples and multi-source features. Multi-layer SEN (MLSEN) strategy is used to simulate the domain expert cognitive process. Genetic algorithm and kernel partial least squares are used to construct the inside-layer SEN sub-model based on each mechanical vibration and acoustic frequency spectral feature subset. Branch-and-bound and adaptive weighted fusion algorithms are integrated to select and combine outputs of the inside-layer SEN sub-models. Then, the outside-layer SEN is constructed. Thus, "sub-sampling training examples"-based and "manipulating input features"-based ensemble construction methods are integrated, thereby realizing the selective information fusion process based on multi-condition history samples and multi-source input features. This novel approach is applied to a laboratory-scale ball mill grinding process. A comparison with other methods indicates that the proposed MLSEN approach effectively models mechanical vibration and acoustic signals.

1. Introduction

Accurate measurement of difficult-to-measure key production quality and quantity parameters within heavy mechanical devices, such as load parameters of a ball mill in the mineral grinding process, is essential for operational optimization control of complex industrial processes [1]. However, the first principal models for measuring these process parameters are difficult to construct due to the complex working mechanism of these industrial processes. Moreover, the rotate working

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characteristics of these mechanical devices, such as ball mills, cause difficulty in measuring these process parameters with direct measuring methods [2,3]. Mechanical devices of complex industrial processes produce strong vibration and acoustic signals. However, in the time domain, valuable information relative to difficult-to-measure process parameters are buried in a wide-band random noise signal known as white noise [4]. Studies show that high-dimensional frequency spectra contain useful information for measuring these process parameters [5–7]. Thus, mechanical vibration and acoustic frequency spectra have been used for process monitoring and modeling [8–10], such as load parameter modeling of a ball mill in the grinding process. In the practical industrial process, domain experts can efficiently monitor the process parameters of familiar mechanical devices by considering interesting information that originated from different operating conditions and multiple sources. Thus, the development of reliable online sensors has become one of the bottlenecks and challenges in simulating human cognitive behavior. Data-driven soft-sensing technique, as one of the major solving methods, has been used in broad fields due to its inferential estimation capability [11–13]. This study focuses only on mechanical vibration and acoustic signals to model difficult-to-measure process parameters.

Theoretically, mechanical vibration and acoustic signals of industrial mechanical devices have non-stationary and multi-component characteristics. For example, a ball mill is a heavy high-energy-consuming mechanical equipment [14]. A ball mill contains millions of balls arranged in different layers. These balls impact mineral ores and mill inside lines with different impact forces and periods, thereby producing multiple mechanical sub-signals with different time scales. The normally measured strong shell vibration signal is mixed with these multi-scale sub-signals. Shell vibration is just one of the main sources of the measured acoustic signals near the mill grinding zone. Domain experts can select useful multiple operating conditions and multi-source features to make final decisions. In the practical grinding process, the acoustic signals are always used by experts on the basis of their acoustic perception. In nature, human ears act as bandpass filters, which can discern useful information from such multi-component signals. Moreover, the human brain has a multi-level structure. Simulating the expert cognitive process remains a difficult open issue. Signal processing techniques are commonly used to analyze these mechanical signals [15]. The transformed frequency spectra of mechanical vibration and acoustic signals contain useful information relative to difficult-to-measure process parameters [16]. Thus, to simulate expert cognitive process, at least three sub-problems should be focused on, namely, time/frequency domain transform, high-dimensional spectral feature reduction, and soft measuring model, in terms of selective fusion multi-condition samples and multi-source features.

The normally used time/frequency transform method uses fast Fourier transform (FFT) on original mechanical vibration and acoustic signals. In [17], frequency spectra are considered single scale. However, these mechanical vibration and acoustic signals have non-stationary and multi-component characteristics. The FFT may be unsuitable in processing such mechanical signals [18]. Some time/frequency analysis methods, such as discrete wavelet transform, continuous wavelet transform, and wavelet packet transform, have been used for such mechanical signal-based fault diagnosis and image processing [19–25]. However, a suitable basic function has to be selected for any practical problem. Empirical mode decomposition (EMD) and its variants can overcome this problem by obtaining a set of intrinsic mode functions (IMFs) [26,27] in terms of the frequency distribution of different sub-signals, which have been successfully used in different industrial processes [28–32]. These IMFs can be considered multi-source information that represents different sensors [33]. However, the number of valued IMFs is limited. Moreover, different process parameters relate to different sub-signals. The FFT is also employed to address sub-signals with different time scales, which have been applied in bear fault diagnosis and ball mill shell vibration analysis [34,35]. These IMF-based frequency spectra are characterized by different scales and are thus called multi-scale frequency spectrum. From the perspective of the components of mechanical signals, the single-scale frequency spectrum contains global information, and the multi-scale frequency spectrum contains different local information with detailed physical interpretation. However, the single-scale frequency spectrum can be used to extract or select feature subsets with different types of information. For example, the shell vibration frequency spectrum can be divided into at least three parts, namely, the natural frequency bands of the ball mill and its inside load, the main impact frequency bands of balls to mill liners, and the secondary-impact frequency bands of balls to balls and other impacts [36]. From the viewpoint of the mechanical signal components, the multi-scale frequency spectra can be considered feature subsets with different local information. Theoretically, multi-scale frequency spectra based on different IMFs can construct a soft sensor model with a more reasonable explanation. However, this complex signal decomposition process can lead to uncertain and inaccurate information. Normally, FFT-based single-scale frequency spectrum is the most widely used spectral data in practical industry.

This finding shows that the single-scale and the multi-scale frequency spectra include hundreds or thousands of frequency variables with a high-frequency resolution (e.g., 1 Hz). Two approaches, namely, feature selection and feature extraction, can be used to address the dimension reduction problem. Mutual information (MI)-based feature selection is a more comprehensive approach than the others [37,38]. However, discarded variables may decrease the generalization performance of the estimation model. Feature extraction method can determine an appropriate low-dimensional data from the original one. Principal component analysis (PCA) is one of the normally used methods with different backgrounds [39,40]. The kernel PCA method is one of the simplest and most elegant approaches to address the nonlinearity of industrial processes [41–43]. Most studies indicate that global feature extraction can obtain better classification accuracy [44,45]. In nature, manifold space learning is also a feature extraction method [46]. Normally, selected or extracted features are used to construct soft sensor models based on statistical inference and machine learning techniques [47–50]. Some incremental learning algorithms have been proposed to address the long learning time problem of these methods [51,52]. However, the above methods take dimension reduction and model construction as two different phases. Moreover, the extracted features from PCA do not take into account the correlation between input and output variables [53]. Projection to latent