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Compressed sensing based on dictionary learning for extracting impulse components

Xuefeng Chen*, Zhaohui Du, Jimeng Li, Xiang Li, Han Zhang

State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, 710049 Xi'an, China

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ABSTRACT

It is essential to extract impulse components embedded in heavy background noise in engineering applications. The methods based on wavelet have obtained huge success in removing noises, leading to state-of-the-art results. However, complying with the minimum noise principle, the shrinkage/thresholding algorithms unreasonably remove most energy of the features, and sometimes even discard some important features. Thus it is not easy to guarantee satisfactory performance in actual applications. Based on a recently proposed theory named compressed sensing, this paper presents a new scheme, Sparse Extraction of Impulse by Adaptive Dictionary (SpaEIAD), to extract impulse components. It relies on the sparse model of compressed sensing, involving the sparse dictionary learning and redundant representations over the learned dictionary. SpaEIAD learns a sparse dictionary from a whole noisy signal itself and then employs greedy algorithms to search impulse information in the learned sparse dictionary. The performance of the algorithm compares favourably with that of the mature shrinkage/thresholding methods. There are two main advantages: firstly, the learned atoms are tailored to the data being analyzed and the process of extracting impulse information is highly adaptive. Secondly, sparse level of representation coefficients is promoted largely. This algorithm is evaluated through simulations and its effectiveness of extracting impulse components is demonstrated on vibration signal of motor bearings. The advantage of SpaEIAD is further validated through detecting fault components of gearbox, which illustrates that SpaEIAD can be generalized to engineering application, such as rotating machinery signal processing.

1. Introduction

Rotating machinery covers a broad range of engineering equipment and plays an important role in many industrial applications, such as wind turbines, aircraft engines and power plants. A serious failure may result in catastrophic incidents and significant economic losses. Structural health monitoring (SHM) of rotating machinery, based on the acquired condition monitoring data [1,2], is very important for identifying potential failure, evaluating operational status and forecasting the probability of reliable operation. In case of structural health degradation, the corresponding vibration signals will present variations induced by the underlying failure. Vibration signal analysis has long been a basic approach for condition monitoring of rotating machinery. However, the complex and non-stationary vibration data with a large amount of noise make the failure detection very challenging, especially at the early stage. By means of appropriate vibration signal processing, it is feasible to detect the failure to evaluate the operational conditions qualitatively and quantitatively.

The measured vibration signals often contain noises, which may arise due to sensor imperfection, poor surrounding environment, or communication errors. Useful features information is therefore usually too weak to be

* Corresponding author. Tel.: +86 29 82663689.
E-mail addresses: chenxf@mail.xjtu.edu.cn, xjtuchenxf2010@163.com (X. Chen).

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distinguished. Removing such noises is of great benefit in successive applications. Much attention has been paid to signal denoising in the past two decades, with various algorithms and principles. The multi-resolution analysis performed by the wavelet transform has been proven to be a powerful tool in denoising a signal corrupted by Gaussian noise. After the pioneering works by Donoho and Johnstone [3,4], a variety of shrinkage methods based on classical models or Bayesian statistical models in the wavelet domain have been proposed and studied broadly, for example, in [5–19]. VisuShrink [3] uses a near-optimal shrinkage rule in the minimax sense and provides the optimal threshold value $T=\sqrt{2\sigma^2 \log N}$, where σ is the noise variance and N is the number of samples. SureShrink [4] minimizes Stein's unbiased risk estimator (SURE) [20] to choose the optimal threshold, which is a data-driven subband adaptive technique. An extensive review of the classical and empirical Bayes wavelet shrinkage/thresholding estimators is provided in [19].

The extraction of impulse components from noisy signals has been one of the essential techniques [5–11]. When rotating machinery develops faults, impulse signals contain a large amount of operating information and serves as a vital indicator of structural health. Failures (such as cracks, flaking, abrasion) of rotating machinery components often generate impact force in every collision. In practice, due to the inertia of rotating machinery, the impulse exponentially decays in the form of damped oscillation, but does not immediately returns to equilibrium when a shock force

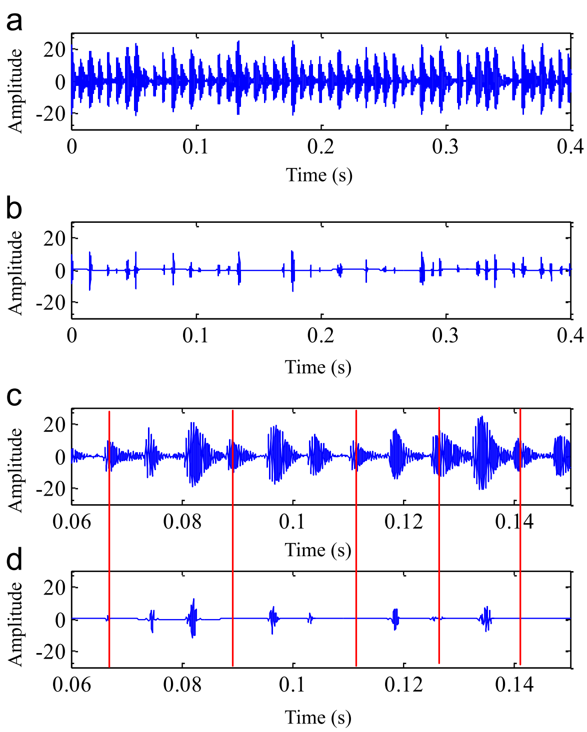

Fig. 1. Examples of rolling bearings with an outer-race defect and using classic SureShrink algorithm (symmlet 8 wavelet basis): (a) vibration signals of rolling bearing; (b) purified signals using SureShrink; (c) the original details between 0.06 and 0.15; (d) the purified details corresponding to (c).

disappears [9]. An impulse signal measured on a bearing with an outer-race defect is displayed in Fig. 1(a). The impulses are generated when the rolling elements pass the defect on the outer-race, and the period is the interval between the two balls passing the defect. As is shown, each impulse has a decaying duration as displayed by the local details in Fig. 1(c), but not a single vertical line. As noise level in the impulse signal is nearly zero, additive white noises with signal-to-noise ratio (SNR) of 1 are added into the impulse signal to test the performance of shrinkage/thresholding method. The SNR is the ratio of the standard deviation of the signal to that of the noise. The purified impulses using SureShink are also shown in Fig. 1(b). Fig. 1 (d) is the purified details corresponding to that of Fig. 1(c). Comparison between Fig. 1(c) and (d) reveals that the method removes too much energy to reduce noises completely and even some impulses as indicated by the red lines. Although the shrinkage/thresholding algorithm has many encouraging theoretical properties, the results obtained tend to be smooth lines (similar to various simulation signals, such as Doppler, HeaviSine, Bumps) as the mathematicians construct. The ideal signals, which many engineers desire, are far from those linear signals with few features information but preserve the most feature energy and details with acceptable noise level.

Compressed sensing (CS) that emerged in 2005–2006 [21–23] breeds a new method to extract impulse signal from heavy noises. The core theory of the CS model is the sparse representations/approximation. Over the last several years, there has been an explosion of interest in the sparse representations/approximation of signals over redundant dictionaries [24–27], especially after the emergence of CS. Sparse representations/approximation problem with sparsity-inducing norms consists in approximating signals using linear combinations of a small number of waveforms or atoms in a redundant dictionary. CS lies on the assumption that it is possible to reconstruct a sparse signal exactly from only a few samples, namely solving an underdetermined linear system of equations [24]. Donoho and Candes make enormous contributions to the theory and algorithm in this field [23,28–33]. Eldar and Duarte [34] introduce the concept of structure into CS matrices and propose X-sampling. Single pixel imaging [35] and compressed sensing MRI [36] validate the feasibility of its practical applications. In the past few years, there have been tremendous progresses in the theoretical development and algorithmic design, so that it is a work of Hercules for anyone who attempts to review all the vast achievements. Excellent review articles are recommended such as [23,34,37,38].

The fundamental idea of CS is that the signal must be sparse enough in the corresponding dictionary to recovery all the important information. A basic problem is the choice of the dictionary [39] that sparsifies the signals. The majority of literature on this topic can be divided into two classical categories: the analytic approach and the learning-based approach. In the first approach, a mathematical model of the data is formulated, leading to an implicit dictionary based on the known fast transforms and their variations. These dictionaries are highly structured and have fast implementation with $O(n)$ or $O(n\log n)$ computational cost. Dictionaries of this type include