Nonlinear Signal Classification based on Wavelet Transform and Deep Belief Network

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Abstract. In recent years, the analysis of EMI (Electromagnetic interference) signals has become a hot research topic in the signal processing field. Particularly, EMI signal classification has attracted more and more attention. Conventional signal classification methods usually select features by experience or implicitly by the shallow artificial neural network, and always results in bad performance on high-dimensional and nonlinear EMI signals. This paper proposed a novel classification method based on wavelet transform and deep belief network, while wavelet transform method is used to reduce the dimension of high-dimensional signals and deep belief network can extract nonlinear features from EMI signals. Then we apply BP neural network as the classifier. Results on the benchmark dataset have shown the superiority of the proposed method compared with the state-of-the-art approaches.

1. Introduction

The problem of EMC (Electromagnetic Compatibility) is always one of the hottest research topics in the signal processing field. The precision and accuracy of the EMI factors analysis will have a certain deviation and uncertainty, and we cannot accurately diagnose various interference factors. EMI signals have the properties i.e. high-dimensional, strongly nonlinear, and non-stationary characteristics. Therefore, we can take actions to reduce impacts if we identify correctly. Actually, classifying an unknown electromagnetic signal is a signal classification problem. Signal classification is to classify signals into its most similar existing categories according to some criteria. In the field of security, we can classify an audio signal to identify the speaker so as to potential target [1]. In the medical field, classifying EEG signals efficiently can help doctors make a definite diagnosis of the type [2].

We often divide signal classification processing into three steps: preprocessing, feature extraction, and classification. Preprocessing is a bundle of methods that can normalize data so as to make it convenient for latter process. Feature extraction is the most essential step in signal classification. It is difficult to classify the original signal data with noise. As a matter of convenience, we transform signals into another equivalent structure to help classify. We call this kind of structure “Features”, which is the foundation of signal classification. Finally, after extracting features, we can evaluate the similarity of the two signals to carry out the process of classification.

For conventional feature extraction approaches, some algorithms such as PCA (Principal Component Analysis) [3] and spline interpolation [18,19,20]. Rivero D et al. [4] apply Fourier transform to signals, and use a Genetic Algorithm to find the most representative statistics in different frequency band, such as mean value and variance as a feature, to input into the KNN algorithm. Mohimani H et al. [5] combine the coefficients decomposed by wavelet transform and features generated by PCA as new features, to cluster and classify with fuzzy C-means algorithm. For unlabeled signals, we can apply unsupervised learning [6], such as SOM (Self-Organized Feature Map
Network). SOM clusters signals that have similar features by determining cluster centers. Statistical classification is another popular feature space classification method. L Bruzzone et al. [7] proposed a "structured neural network" based on MLP with hierarchical sparse features. Combining two artificial neural networks was proposed by Elif Derya Übeyli [8].

Conventional methods listed above can only process low-dimensional or linear signals but not the other one [9]. Inspired by the recent success of deep learning in various research fields [13,14,15,16,17], we propose a novel signal feature extraction method based on wavelet transform and DBN (Deep Belief Network), to further promote the research of high-dimensional nonlinear signal classification. As much noise of high-dimensional nonlinear EMI signals are known, we apply multi-scale decomposition to original signals and get low-dimensional signals. Then we put the coefficients as input data into DBN to extract nonlinear features. In the meantime, we add a BP (Back Propagation) neural network at the top of the DBN. Next, we use fine-tuning to train the whole DBN system with features extracted before. After the training, the DBN and the classifier can be used to feature extraction and classification on the condition that signals should be applied with wavelet transform first. Signals after wavelet transform can reduce the energy of noise significantly and can still keep the feature of original signals.

There are mainly two advantages that we use DBN to extract features. Firstly, we train each layer of the unsupervised network separately, so that we can ensure keeping features as many as possible when vectors are reflected in the space. Secondly, the process of DBN training can be taken as an initialization of the deep BP network parameters. The reason is that DBN could make BP network overcome the disadvantages of falling into local optimum and long training time due to the random initial weighted parameters.

The remaining parts of this paper are organized as follows: Section 2 describes the novel method proposed above, which consists of feature extraction and classifier. Section 3 describes the performance of the method, and Section 4 is the conclusion.

2. Approach
For the method proposed in this paper, we apply multi-scale wavelet transform into original signals to reduce the dimension. Then we apply wavelet coefficients as compressed features to DBN. This step will extract feature representations that are used for classification. Finally, we use the BP network to do supervised classification. The method framework shows below in Fig. 1. It contains two parts: the feature extraction learning phase and the classification learning phase.

![Figure 1. Framework of signal feature extraction and classification technology.](image_url)

2.1. Algorithm Introduction
According to the framework of Fig. 1, this algorithm has two steps: one is feature extraction, the other is classification. Following is the concrete algorithm flow:

2.1.1. Feature extraction.
- Apply wavelet transform to original signals so as to keep features of original signals.
- Input wavelet coefficients from step 1 into DBN to learn nonlinear and higher-level features.
2.1.2. Classifier learning.
- Features which extracted from DBN are taken into BP network to do supervised classification.
- Use fine-tuning method to process the error signal transporting from top to bottom RBM (Restricted Boltzmann Machine) and improve the classification performance.

![Multi-scale analysis](image1)

2.2. Feature Extraction
The following describes wavelet transform and DBN.

2.2.1. Wavelet transform: Wavelet analysis is fast attenuation to represent a signal with finite length. This kind of waveform can match the input signal with scaling and translation. Compared to Fourier transform, wavelet transforms are localized in the time domain and frequency domain. The multi-scale wavelet transform uses steps to process at most. At each phase, input signals are divided into two parts: low-frequency part and high-frequency part. Then two parts are down-sampled to half of the original length and generate two coefficients, such as approximation coefficients and detail coefficients. Approximation coefficients are the estimate of the raw input signal. They retain the basic features of input signals. Detail coefficients mainly contain some high-frequency composition, such as noise. Then approximation coefficients are used as input of the next phase to do further processing. As shown in the subplot (a) of Fig. 2, the original signal has a dimension of 4096×1. The subplot (b) of Fig. 2 shows the approximation coefficients after five phases of multi-scale wavelet analysis. It's a signal with a dimension of 129×1. We can observe that despite the dimension of the output signal is much less than the dimension of the input signal, the basic feature of the original signal can be retained. The noise component is largely reduced.

2.2.2. Deep Belief Network: A deep belief network is a generative model containing a multi-layer neural network. Specially speaking, the high efficient training process of RBMs makes RBM an appropriate component to DBN. Each layer of hidden units in RBM learns and represents characteristics of original input data. The basic idea of DBN is to extract and abstract input data from the bottom to each layer RBM and retain important information as far as possible. DBN is a kind of neural network with trained initial weights.

2.2.3. Classifier Learning: DBN network used in this paper consists of some layers of RBM and one layer of BP network. The process of training the DBM model is divided into two parts:
- Step one: Training each layer of the RBM network separately can make sure vectors can retain information as far as possible when reflected in different feature spaces.
- Step two: Adding a BP network to the topmost layer of DBN. The BP network will receive the output feature vectors of RBM as its input and train the classifier. Each layer of the RBM network can only make sure that the reflection from the inner layer's weights to this layer's feature vector is the best but not to the whole DBN's feature vector. So the error information of the BP network will be transformed from top to bottom's RBM, and the DBN will be fine-tuned. The RBM training model
process can be treated as initialization to a deep BP network's weights, which can help DBN overcome the disadvantages of local optimum and long training time.

The first step of the above model is called pre-training of the network, and the second step is called fine-tuning. The topmost of the network can be any classifier model according to a specific research area but does not have to be a BP network.

3. Results
To validate the performance of the proposed method, we conduct comparison experiments on EEG signals. EEG signal is the recording of electrical activity along the scalp. It has an obvious character of high dimension and nonlinear, and it also includes a lot of noise. The signals are very vulnerable to have interfered with surroundings. Therefore, EEG signals are very similar to actual EMI signals. According to the EEG signals analysis, we can make a definite diagnosis. Thus EEG signals have an important practical value. The dataset comes from Delorme [10]. It has 500 items, 200 of them are signals from healthy people, and 300 of them are signals from epileptic people. Each item records the EEG signal of a certain active state that the human brain presents. As shown in the following figures. Fig. 3 is two signal subplots of healthy people. Fig. 4 is three signal subplots of epileptic people.

Now let's divide all the data into two groups. One group with 400 items is training data. The other group with 100 items is testing data. Each signal is a vector of $4096 \times 1$. With the multi-scale wavelet decomposition, we set the layer number be 5. After the decomposition, the size of the vector is $129 \times 1$. Finally, we use the data from the previous method as the input data to DBN and BP network. The training network is applied to the testing dataset. Compared with state-of-the-art approaches, the accuracy of DBN(RBMs+BP) is 92%. However, the accuracy of Softmax regression [11] and SVM (Gaussian kernel) [12] are 87% and 82%.

To verify the robustness of the classifier, we adopted the approach of 10-fold cross-validation. The result of classification presents the median of the classification accuracy. For comparison, we compare our method to another baseline: Support vector machine (SVM) with Gaussian kernel and Softmax.
What calls for special attention is that we still need to apply wavelet transform to data before using these classifiers. We find that DBN with the fine-tuning process has a better result than SVM and softmax regression. The reason may be that SVM supports better for binary classification problems but worse for multi-class classification. In addition, softmax regression cannot extract nonlinear features from signals and cannot classify accurately.

4. Conclusion
In this paper, we proposed a high-dimensional nonlinear signal classification method based on wavelet transform and deep belief network and elaborated the steps of this method. We show that the multi-scale wavelet analysis can decrease high-dimensional signals to low-dimensional and keep the original signal features at the same time. We use a deep belief network to extract nonlinear features from wavelet coefficients, and a BP network to classify them. We apply this method to practical EEG signals and compare it to other methods. The results indicate that this method yields better performance, assessing its effectiveness and reliability.

Acknowledgements
This work was supported by the National Natural Science Foundation of China under Grant 61771001.

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