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A One-stop Method for EMI Analysis Based on Wavelet Packet and SOM

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Abstract. The analysis of electromagnetic interferences (EMI) has been a heated problem in the field of Electromagnetic Compatibility (EMC). As the demand of efficiency and effectiveness is getting higher, the traditional methods have become the short board in analysis process. These methods haven't provided a solution to analyze the relation among multiple EMI signals, and the data clustering and mining are currently done manually. To address this problem, in this paper we propose a one-stop method based on the wavelet packet decomposition (WPD) and self-organized feature map (SOM), aiming to provide a systematical and solution to extract and analyze multiple EMI signals. Experimental results are also provided to demonstrate the validity and efficiency of the proposed method.

Introduction

In the design of modern electronic systems and integrated chips, the electromagnetic compatibility is affected by the selection of components and devices, PCB floor planning [3, 6] and etc. In order to design a robust system, the designers would try different combinations and test their performances [5]. In this process, signal data are sampled and analyzed to evaluate the EMC, which involves extracting and analyzing interesting EMI features from original signals. In terms of feature extraction, the traditional methods, taking FFT for example, assume that input signals are stationary, which could fail in dealing with non-stationary and nonlinear data. Many works have been done to improved existing algorithms, such as the Genetic-Algorithm-based method [1], RBF-based modeling method [2], and FDTD [4]. However, to the best of our knowledge, how to analyze multiple mixed EMI signals has not been discussed so far. To address the problem, we propose a novel method based on the combination of WPD and SOM, which provides a unified one-stop tool for signal feature extraction and analysis.

We use the WPD to extract interesting signals. To cluster and analyze EMI signals, we adopt the self-organized map (SOM).

The One-stop Method Based on WPD and SOM

Wavelet and Wavelet Packet.

Due to its better retractility and flexibility, as well as the ability to processing nonlinear and non-stationary data compare to FFT, the WPD is widely used in field of signal processing and image compression. Before describing its working principle, we first introduce the discrete wavelet transform (DWT).

The concept of the wavelet packet is proposed as an improvement to DWT. Each time DWT only decomposes the low-frequency signal to obtain the next level. While, WPD decomposes both high and low frequency signals. When the decomposition is done we will obtain a full binary tree. Then, algorithms based on certain criteria (e.g., classical entropy-based criteria) [5] are applied to select the best decomposition tree. Finally we obtain the best tree, of which the structure is analogous to the outputs of DWT. Compared with DWT, WPD improves the frequency-domain resolution in high frequency and the time-domain frequency in low frequency.

Self-organized Feature Map

The SOM is originally proposed by Kohonen 1981, inspired by the competitive activated expression after certain stimulation of cortical neurons [6].

Typically, SOM is composed of two parts: the input layer and the competitive layer. The commonly used topologies of competitive layer have a one, two or three dimensional structure. In this paper, we mainly focus on the two dimension topology.

Ideally, after the training step, neurons have been self-organized and clustered into several certain zones. The distribution of neurons in two-dimensional plane could be seen as the projection of input data topology in the hyperspace. Therefore we can analyze the relation of input patterns through analyzing the topology

The Proposed One-stop Method

Extracting EMI signals from original signal by using WPD serves as a preprocessor in the one-stop method. The task in this step is to extract the interesting EMI signals, and reduce the dimension to compress each EMI signal into a feature vector.

Here we take an example to illustrate the process. As shown in Fig.1, the signal data is sampled from the power supply of a frequency synthesizer (data are preprocessed and contain only AC signal, the values of voltage are normalized), which comprises 100,000 sampling points.

We decompose the original signal with WPD by setting wavelet function as ‘db6’, decomposition depth n as 8. To keep it uncluttered and without loss of generality, the detail coefficients $d_{2,1}$, $d_{4,1}$, $d_{5,1}$, $d_{6,1}$, $d_{8,1}$ (correspondingly the coefficient are at level 2, 4, 5, 6, 8), and approximate coefficient $d_{8,0}$ are illustrated in Fig.2.

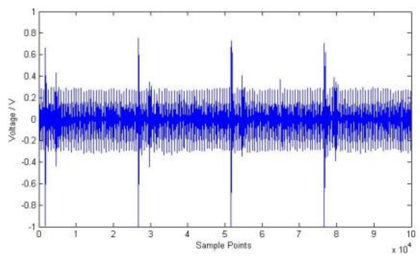

Fig.1 Original signals

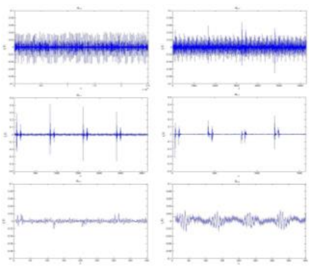

Fig.2 Detailed decomposition coefficients and estimated coefficient

The essential properties of the signal at level i are contained and represented by $d_{i,1}$ [7]. To determine the interesting signals, we calculate the energy E_i at each level, and exclude the signal with small energy. Next, we introduce the unbalance parameter α and the mutation parameter β to evaluate the degrees of unbalance of a signal [12]: $\alpha = \dfrac{\max E_i}{(\sum_{i=1}^{5} E_i)/5}$, $\beta = \dfrac{E_i}{\sum_{i=1}^{5} E_i}$.

When interesting EMI signals are found, we compress them into feature vectors, which consists of signal energy, estimators α, β and other statistics.

After compression, we apply SOM and take vectors as inputs, and the result of cluster analysis will be shown by neuron distance graph and sample distance graph. We can identify cluster centers through the analysis of these two graphs, and then count neurons that belong to different classes.

Experimental Results

Methods for comparison

For comparison, we illustrate the process of analyzing data with traditional methods, i.e., the Short-Time Fourier Transform (STFT) to process the signal.

Since the STFT is designed to process signal one at a time. Without losing generality, here only one example is demonstrated. We perform the STFT to the same signal data in section II, and the spectrum are illustrated in Fig.3. From observations, we can identify and extract EMI signals. Fig.4 illustrates the extracted result, which is basically the same as that extracted by WPD.

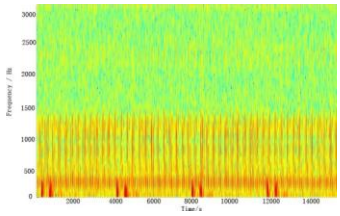

Fig.3Spectrum by using STFT

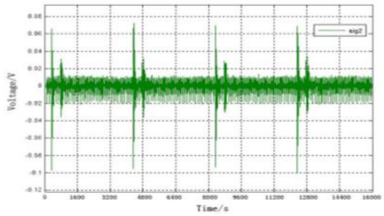

Fig.4 EMI signals extracted by digital filters

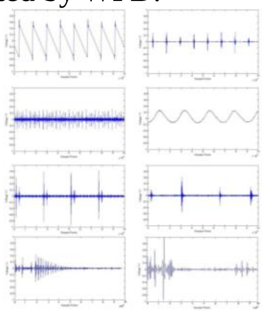

Fig.10 Shows 8 signals indicating 8 categories of EMI signals in sample signal.

The Proposed Method

To evaluate the one-stop method, a set of simulation data are inputted, which comprises 158 original sample signals. We set depth, wavelet function as 8 and ‘db6’, competitive layer neurons as 10×10, and apply the one-stop method. The cluster result is illustrated in Fig.5 and Fig.6. Fig.7 illustrates the partition for the input data. We number the classes and plot the topological map of different classes in Fig.8. The final classification results are shown in Table.1. The EMI signals from class 1 and 6 are illustrated in Fig.9 (only 8 from each class are shown). We could see that signals that belong to the same class have good similarity and signals from different class are distinguishing.

Fig.10 illustrates EMI signals in which each represents one class in Table.1 (exclude classes that have no cluster center such as 9,12,14). These signals are contained in sample data, and could be confirmed to be generated from different EMI sources, this result could be directly used for researchers to improve the electronic system.

Discussion

The procedure of traditional method introduced in previous section could be divided into several parts: (1). For each sample signal, apply the STFT with suitable resolution; (2). Observer and identify EMI signals in spectrogram, extracting them with filter; (3). Manually analyze the EMI signals.

As indicated in previous sections, Manual work is required in all 3 steps above. Additionally, the time performing first 2 step is linear with input data size, making it less efficient.

Specially, the one-stop method consists of the following steps: (1). For each sample signal, apply the WPD, identify the EMI signals and extract them based on certain criteria; (2). Compress the signal into feature vector; (3). Cluster the data with SOM; (4). Identify the cluster centers and partition the data on feature map; (5). Count and classify the data.

For one-stop method, only the partition step needs to be done manually, and the operation within this step only needs to be performed once. In this simulation test, we ran the one-stop method and the average time cost to complete the analysis(exclude partition step) is within 10s (OS environment: Windows7 x64, hardware environment: E3-1230v2，8GB RAM). Therefore, compared with current method, the efficiency of analyzing the data is improved by adopting one-stop method.

From the perspective of effectiveness, the process of EMI signal extraction using STFT is affected by various factors including subjectivity and prior knowledge as long as it is done manually. On the other hand, the solution to situation where multiple sample signals need to be analyzed is not provided in it, this process is currently done manually.

In one-stop method, we adopt the SOM to analyze the multiple EMI signals, making the process automatic and objective. Another result we can obtain from feature map, is the projection of topology of data in hyperspace. In Fig.9 for example, class 1 is relatively closer to class 2 than to class 7, this indicates that the data pattern represented by class 1 is more similar to class 2 than to class 7. This characteristic provides an alternative way to take insight into input data feature.

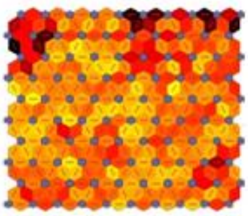

Fig5.Distribution of neurons in hyperspace

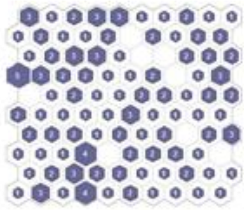

Fig.6Sample hits in feature map.

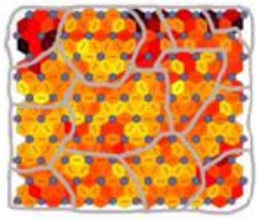

Fig.7 Partition of input data based on the feature map

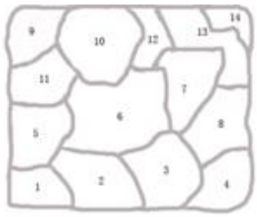

Fig.8 Distribution of classes on the feature map

class	EMI signals
1	4,26,32,33,118,46,9,48
2	3,29,35,36,43,72,76,21,84,85,119,149,56,73,113,102,103,104,105
3	55,126,117,14,15,16,141,143,142,144,17,19,18,20
4	8,7,81,47
5	111,107,106,109,11,12,91,108,116,94
6	38,40,95,30,31,34,122,1,2,155,156,146,82,83,123,97,137,138,112,5,6
7	145,128,129,148,140,45,99,60,147
8	110,77,78,68,69,70,101,98,44,67,157,158
9	50,89,133,136,51,53,54,52
10	130,131,121,28,39,132,127,152,154,96,135,59,57,58,22,24,23,25,27,10,150,151
11	13,90,114,115,124,125,37,41,66,93,120,92,134
12	74,75,88
13	61,100,139,79,80,42,62,71,86,87,153,63,64
14	65,49

Table.1 shows the classification result of input data.

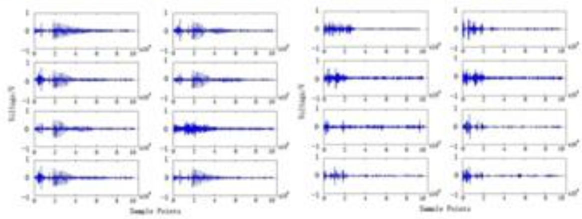

Fig. 9. 8 signals from class 1 (first 2 columns) and another 8 from class 6 (last 2 columns).

Acknowledgements

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