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Research Article

NEW SIGNAL PREDICTION ALGORITHMS TO IMPROVE THE IMAGE QUALITY BY FINDING THE DIFFERENCE BETWEEN THE NOISY AND PREDICTED SIGNAL

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ABSTRACT
In this paper, we develop new EMD based techniques to alleviate the EMD drawbacks. The experimental results demonstrate the ability of this type of decomposition in improving the performance of the existing solutions. We show that Nonlinear Diffusion Filter, one of the most well-known methods for speckle reduction, can be successfully integrated with EMD to suppress the noise. According to the computer simulation results, such fusion is able to remove more noise while keeping more fine structures, which leads to achieving higher PSNR and Bovick values. The results are evident of the ability of the presented approaches to reveal many invisible details. The EME measure confirms the improvement degree as well. A prediction system is implemented based on Neuro-Fuzzy approach. Our ultimate objective is construction of a more reasonable forecasting system with the aid of the EMD solution. First, some background information is presented on time series and forecasting concept. Then, several forecasting tools are listed with the areas they have been applied to. Among all the applications, electric load forecasting and signal denoising are selected to test the proposed prediction algorithms. In order to enhance the efficiency of some existing techniques, Empirical Mode Decomposition (EMD) will be integrated with them.

***Keywords**: EMD, Prediction System, Neuro-Fuzzy, Forecasting System*

INTRODUCTION
Forecasting is the process of making statements about events whose actual outcomes (typically) have not yet been observed. A typical example is estimation for a variable of interest at a particular date in future. Prediction has a similar, but more general definition. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or alternatively to less formal judgmental methods (http://en.wikipedia.org/wiki/Forecasting). In statistics, signal processing, econometrics and mathematical finance, a time series refers to a sequence of values at equally spaced time intervals (http://en.wikipedia.org/wiki/Time_series).
Forecasting the future progress of a system according to the past measured values is a very critical problem in many real situations of life (Mabel and Fernandez, 2008; Senjyu *et al.*, 2002). Time series generating systems can be recognized as stochastic or as deterministic depending on the degree of our a priori knowledge or on our reluctance for one approach or the other. When all the motion equations of a physical system are known, we can integrate them to predict the future states.
This approach generally fails if the number of independent degrees of freedom is high and the system behaves nonlinearly.
To deal with analysis and prediction in nonlinear systems, a number of solutions have been applied, such as Artificial Neural Networks (ANNs), Autoregressive Models (AM), Autoregressive-Moving-Average Modeling (ARMA), Wavelet based methods, Support Vector Machines (SVMs), Least Square SVM (LS-SVM), Support Vector Regression (SVR) and Empirical Mode Decomposition (EMD).
Meanwhile, to achieve a more accurate prediction, EMD is integrated with the other methods. In most of these combined methods, the original data is first decomposed by using EMD. Then, the main prediction technique is applied on each IMF. The signals obtained from this step, then, will be superposed to construct the final prediction signal.

Empirical Mode Decomposition (EMD)

In this section, EMD and EEMD based decomposition algorithms are described in detail. Empirical Mode Decomposition (EMD) is a signal decomposition technique, first introduced by Huang (Çelebi and Ertürk, 2010). The basic idea of this technique is to decompose a signal into a number of frequency oscillations which are called Intrinsic Mode Functions (IMFs). By adding the IMFs and the residue we can reconstruct the original signal without any loss. The sifting procedure is as follows (Qin *et al.*, 2008; Ogier *et al.*, 2007):

Empirical Modal Decomposition algorithm

Input: A signal I

1. Find all the local minima and all the local maxima in the image,
2. Interpolate the local maxima to form the upper surface, $S_{\max}(t)$,
3. Interpolate the local minima to construct the lower surface, $S_{\min}(t)$,
4. Calculate the mean of the upper and the lower surfaces:

$$m(x,y)=\frac{1}{2}(S_{\max}(x,y)+S_{\min}(x,y)) \qquad (1)$$

5. Assign $h(x,y)$ with the difference of original image, $I(x,y)$ and $m(x,y)$:

$$h(x,y)=I(x,y)-m(x,y) \qquad (2)$$

6. Repeat this process K times until $h(x,y)$ is an IMF based on stopping condition, which will be explained later.
7. First IMF, $imf_1(x,y)$ is estimated as:

$$h_{ik}=h_{1(k-1)}(x,y)-m_{1k}(x,y) \qquad (3)$$

$$imf_1(x,y)=h_{1k}(x,y) \qquad (4)$$

8. Subtract $imf_1(x,y)$ from the original image

$$R_1(x,y)=I(x,y)-imf_1(x,y) \qquad (5)$$

9. Treat $R_1(x,y)$ as a new signal and repeat the above procedure n times. The iteration is expressed as:

$$R_n(x,y)=R_{n-1}(x,y)-imf_n(x,y) \qquad (6)$$

Output: imf_i , the IMFs and $R_n(x,y)$, the tendency of I

The original image can be constructed by summing all the IMFs and the residue without any loss.

$$I(x,y)=\sum_{i=1}^{n} imf_i(x,y)+R\ (x,y) \qquad (7)$$

Where $I(x,y)$ is the original image, $imf_i(x,y)$ is the i^{th} Intrinsic Mode Function, and $R_n(x,y)$ is the residue. The first IMF contains highest level of the details in the signal and the residue is the ultimate large scale trend. Despite all the advantages EMD has, it suffers from mode mixing problem

Load Forecasting

Load forecasting is very critical in the electric industry in the deregulated economy. Applications are found in energy purchasing and generation, load switching, contract evaluation, and infrastructure development. Load forecasts can be generally categorized into three classes:

1. Short-term forecasts, normally between an hour to a week;
2. Medium forecasts, basically from a week to a year, and

3. Long-term forecasts which are longer than a year.

Short-term load forecasting is used to estimate load flows and to make decisions which can prevent overloading. By appropriate implementations of these decisions, we can increase the network reliability and reduce occurrences of equipment failures and blackouts. Most forecasting methods work based on statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting. The development and improvements of suitable mathematical tools will result in the development of more accurate load forecasting techniques. The accuracy of load forecasting depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenarios.

Important Factors for Forecasts

In short-term load forecasting, a number of major issues have to be taken into account, such as:
- Customer’s classes,
- Time factors and,
- Weather data

The medium- and long-term forecasts deal with:
- The historical load and weather data,
- Number of the customers in different classes,
- The appliances in the region and their features including age, the economic and demographic data and their forecasts and,
- The appliance sales data

By time factors, we mean the time of the year, the day of the week, and the hour of the day. The load in weekdays and weekends are significantly different. The load also varies between the days of a week. For instance, load on Mondays and Fridays which are close to weekends behaves differently from Tuesday through Thursday. This also holds for the summer time. Since holidays are less frequent, they are more difficult to forecast than non-holidays. Weather factors are the other reasons of load variance. In short-term load forecasting, weather conditions are the most substantial parameters. Temperature and humidity are the most commonly used weather variables for load. Two composite weather variable functions are widely applied by utility companies. One is the THI (temperature-humidity index), a measure of summer heat discomfort and WCI (wind chill index) which refers to the cold stress in winter. The customers of most electric utilities can be categorized into three types: residential, commercial, and industrial customers. Electric usage follows different patterns for customers belonging to different categories while is almost similar for customers in each class.

Medium- and Long-term Load Forecasting Methods

The end-use modeling, econometric modeling, and their integrations are the most common used techniques for medium- and long-term load forecasting.

End-use Models: In the end-use modeling approach, load is directly estimated based on broad information on end-use and end-users, such as appliances, the customer use, their age and sizes of houses. Statistical information on customers and dynamics of change together are the forecast basis. These models focus on the various uses of electricity in the residential, commercial, and industrial sector. They describe energy consumption as a function of the number of appliances in the market. Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast relies less on historical data but more on information about customers and their equipment.

Econometric Models: The econometric modeling is based on the combination of economic theory and statistical methods to forecast electricity demand. Such models estimate the relationships between load and parameters affecting consumption using the least-squares method or time series techniques. One of the options in this framework is to aggregate the econometric approach, when consumption in different classes (residential, commercial, industrial, etc.) is calculated as a function of weather, economic and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioral components into the end-use equations.

Statistical Model-based Learning: The end-use and econometric modeling significantly rely on a large amount of data associated with appliances, customers, economics, and so on. Their application is complicated and human assistance is necessary. Top of all, such information is often unavailable regarding particular customers and a utility keeps and supports a profile of an "average" customer or average customers for different type of customers. The characteristics for particular areas may be different from the average characteristics for the utility and may not be available. To mitigate these problems, a statistical model is developed to learn the load model parameters from the past data.

Short-term Load Forecasting Methods

Many statistical and artificial intelligence approaches have been introduced for short-term load forecasting.

Similar-day Approach: This method looks for days in one, two, or three years in historical data, the characteristics of which are similar to the forecast day'. Such characteristics include weather, day of the week, and the date. Then, the load of the similar day will be treated as a forecast for the day of interest. The forecast can be performed by a linear combination or regression of several similar days. The trend

Regression Methods: Regression is one of the most broadly applied statistical methods. For load forecasting, these methods are often used to model the relationship of load consumption and other parameters such as weather, day type, and customer class.

Time Series: Time series methods assume that there is an internal structure in data, such as autocorrelation, trend, or seasonal variation. These techniques are responsible for detecting and exploring such a structure. Among the time series techniques, the most commonly used ones are:

- Autoregressive moving average (ARMA),
- Autoregressive integrated moving average (ARIMA),
- Autoregressive moving average with exogenous variables (ARMAX) and,
- Autoregressive integrated moving average with exogenous variables (ARIMAX)

The ARMA models are normally used for stationary processes while ARIMA is applicable to nonstationary processes. The only input parameters to ARMA and ARIMA are time and load. Generally, load is a function of weather and time of the day; thus, among time series models, ARIMAX is the most useful tool for load forecasting.

Neural Networks: Artificial neural networks (ANNs) are able to perform non-linear curve fitting. Practically, network elements are connected by a number of layers of neurons, and feedback paths are sometimes used. The parameters required to be taken into account when applying ANNs in load forecasting applications include:

- Selecting a suitable architecture (e.g. Hopfield, back propagation, Boltzmann machine),
- Selecting the number and connectivity of layers and elements,
- Applying bi-directional or uni-directional links, and
- Defining the format of the numbers in inputs and outputs and hidden layers (e.g. binary or continuous).

Back propagation is the most popular ANN architecture in load forecasting applications. In such networks, continuously valued functions and supervised learning are adopted. Through supervised learning, the weights are estimated by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session". Artificial neural networks with unsupervised learning do not require pre-operational training.

Expert Systems: To have an accurate forecast, expert systems use rules that are usually heuristic. The rules are extracted from the knowledge of human experts. The system, then, will be able to automatically forecast without human participation.

Fuzzy Logic: Fuzzy logic is an extension of the traditional Boolean logic. It has an approximate reasoning system rather than a fixed and precise. Unlike the classical logic theory, the truth values of the variables in fuzzy logic can range from 0 to 1. For example, the energy consumption of a transformer may be "low", "medium" and "high". In fuzzy logic, the outputs can be logically inferred from inputs. Using such systems, the need for a mathematical model to map inputs to outputs as well as precise (or noiseless) inputs is eliminated. Thus, fuzzy logic-based systems can be significantly robust in load forecasting tasks.

When using fuzzy logic techniques in load forecasting problem, a few major issues need to be addressed (Chow and Tram, 1997): How to implement linguistic descriptions of the land usage selection and load forecasting in a computer program for decision automation,

- How to combine the available information for decision making purpose.

Support Vector Machines: Support Vector Machines (SVMs), developed by Vapnik in 1995 is based on a statistical learning theory. In contrast with neural networks, which try to define complex functions of the input feature space, SVMs nonlinearly map the data into a higher dimensional (feature) space using kernel functions. Then, they build linear decision boundaries in the new feature space using simple linear functions. The problem of selecting a suitable architecture in ANNs is replaced by the problem of choosing an appropriate kernel function in SVMs.

Neuro-fuzzy Model (Nayaka et al., 2004): Neuro-fuzzy modeling applies different learning techniques developed in the neural network literature to fuzzy modeling or to a fuzzy inference system (FIS). The FIS structure consists of three major parts:

1) A rulebase, containing a selection of fuzzy rules;
2) A database, defining the membership functions (MF) which are applied in the fuzzy rules; and
3) A reasoning system, performing the inference procedure under the rules to obtain an output.

The FIS, nonlinearly maps the input space to the output space using number of fuzzy if-then rules. Each of these rules describes the local behavior of the mapping. The parameters of the if-then rules define a fuzzy region of the input space, and the output parameters specify the corresponding output (Nayaka *et al.*, 2004).

Challenges

Since the relationship between load power and factors influencing load power is nonlinear, it is difficult to identify its nonlinearity by using conventional methods. Most of papers deal with 24-hour-ahead load forecasting or next day peak load forecasting. These methods forecast the demand power by using forecasted temperature as forecast information. But, when the temperature curves changes rapidly on the forecast day, load power changes greatly and forecast error would increase.

Experimental Results for Load Forecasting

As the first step, a load forecasting is performed using a Neuro-Fuzzy model. The result is presented in the following Figure 2. The original signal is plotted in Figure 1. To improve the quality of prediction by the selected model, the original signal is decomposed into its IMFs. Figure 3 presents the IMFs of the signal shown in Figure 1. The prediction algorithm is run on the IMF1, IMF2 and IMF3 as presented in Figure 4, Figure 5 and Figure 6. Then, the three predicted signals are summed up and the result is shown in Figure 7. Still, we have not reached the expected level of prediction. We believe that the parameters of the forecasting algorithm have to be tuned for each IMF separately

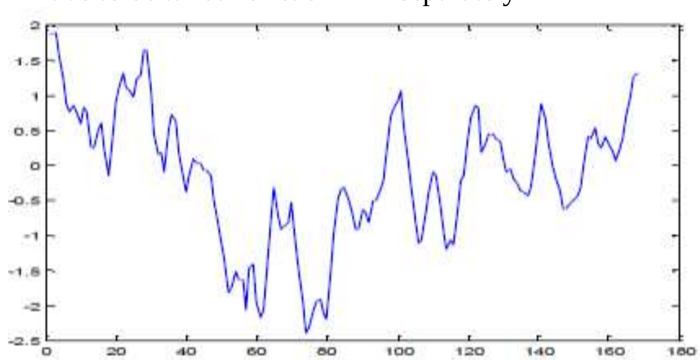

Figure 1: Original load signal

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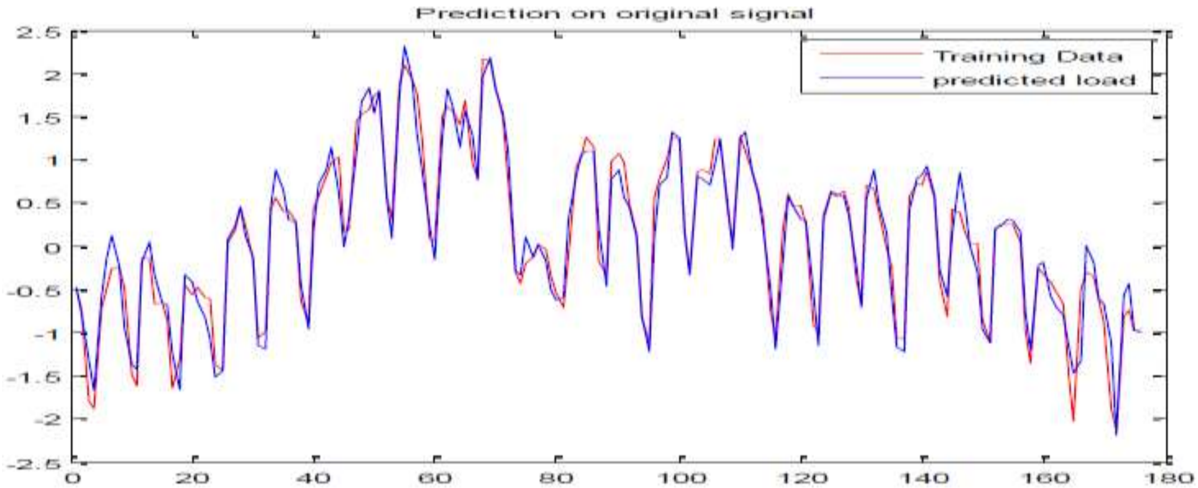
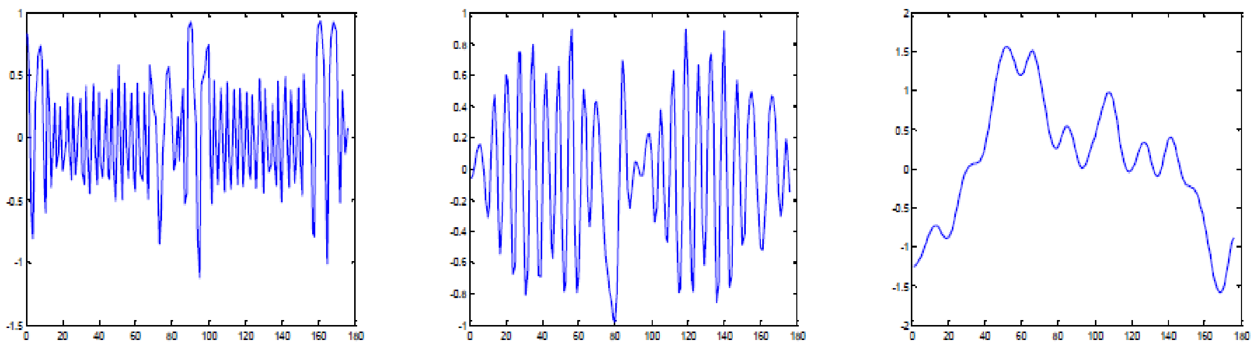


Figure 2: Original and the predicted load signals



(a) (b) (c)

Figure 3: MF1; (b) IMF2; (c) IMF3

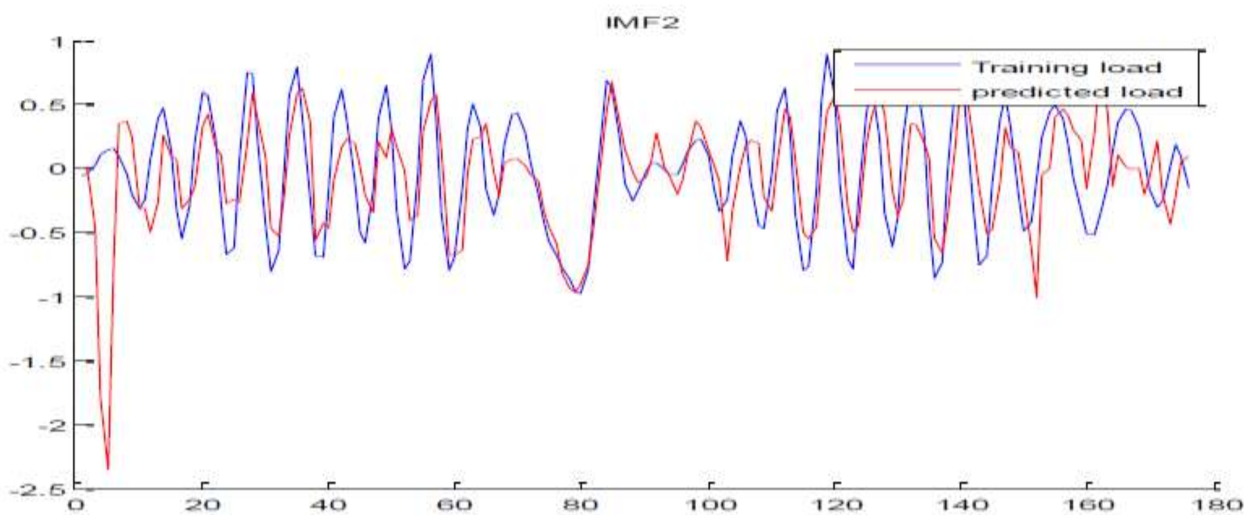


Figure 4: Prediction on IMF1 of the load signal

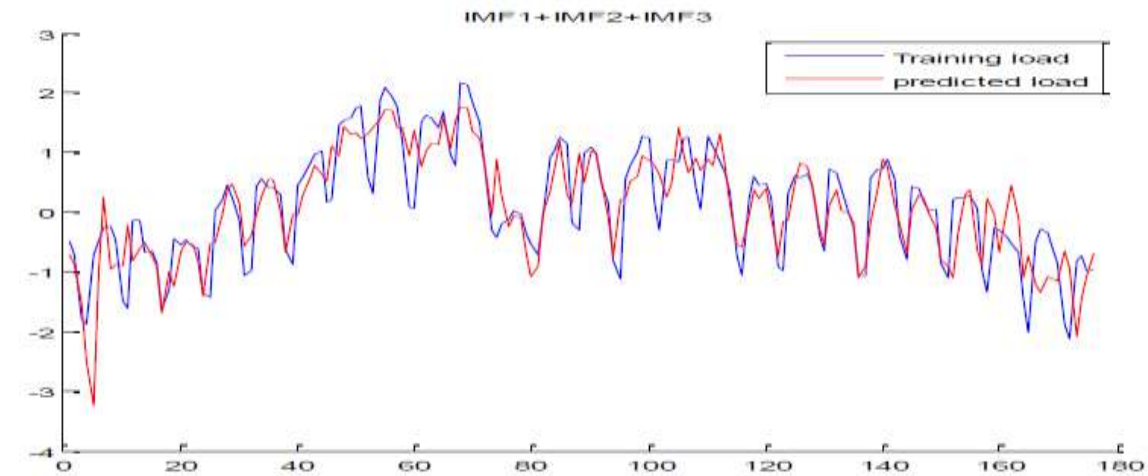


Figure 5: Prediction on IMF2 of the load signal

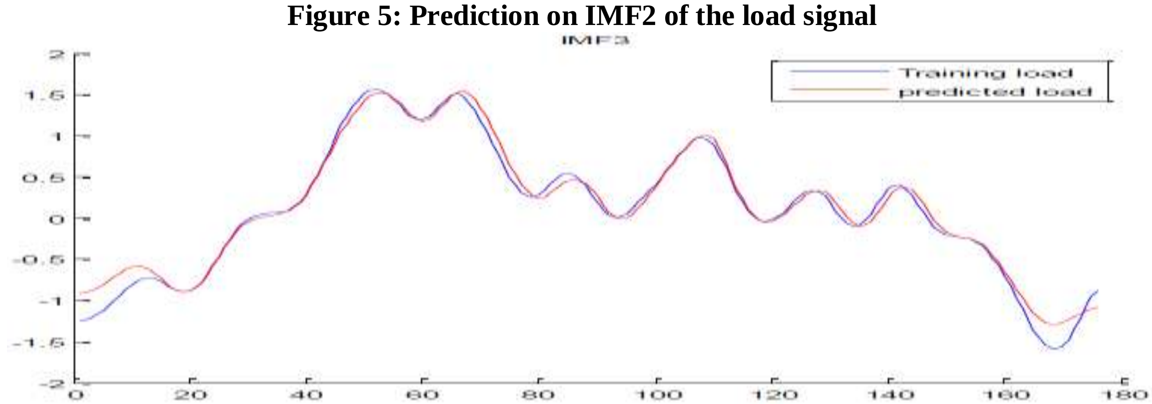


Figure 6: Prediction on IMF1 of the load signal

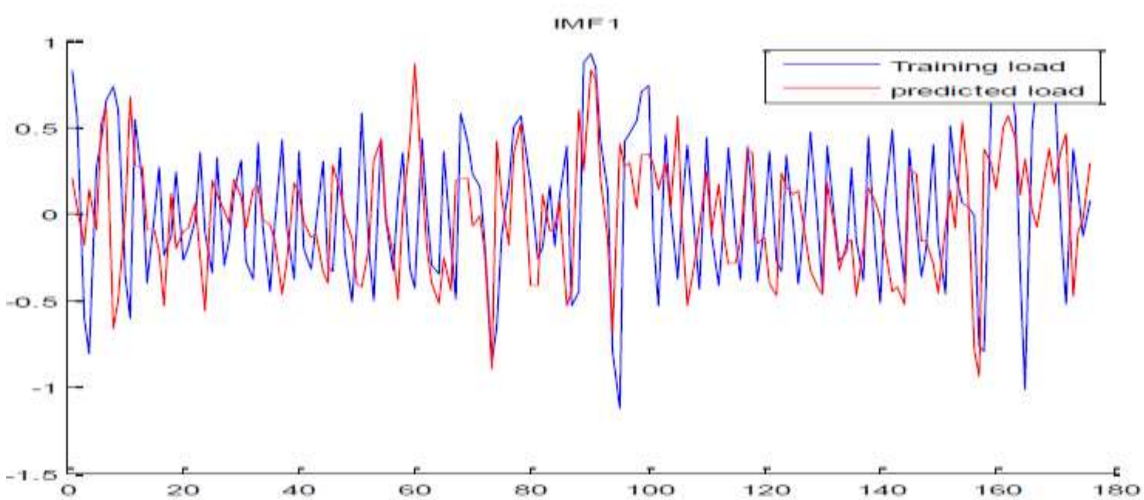


Figure 7: Sum of all the predicted IMF signals

Denoising using Neuro-Fuzzy Prediction System

1D Noise Removal

In this section, we propose a noise removal approach in 1D signals based on signal prediction. In this method, first the Neuro-Fuzzy system is trained using some clean and noisy copies of them. Then, when the test signal is fed to the system, it will generate an almost clean signal as the output. Thus, by finding the difference between the noisy and predicted signal, we can locate the noise. By performing median filter on only the extracted locations, we will appropriately suppress the noise while avoiding over-smoothing. The experimental results show when the median filtering is applied on the whole signal the Root Mean Square Error (RMSE) is greater than when it is only run on the noise regions.

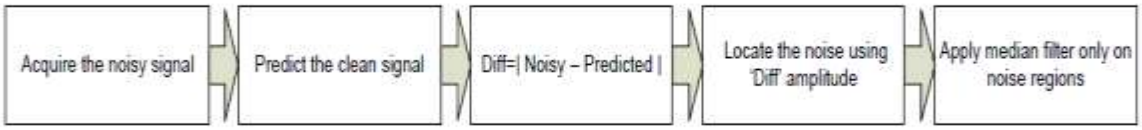


Figure 8: Block diagram of Impulse noise removal using prediction

To remove Gaussian noise, first we predict the clean signal and then, apply a mean filter with an appropriate size on the predicted signal. In the simulation we have used a mean filter with size 4. The size can be adaptively changed based on the local noise level. The results illustrate that the RMSE of the cleaned signal by the new method is less than the RMSE obtained by applying mean filter 4, 7 and 10 on the noisy signal, independently.

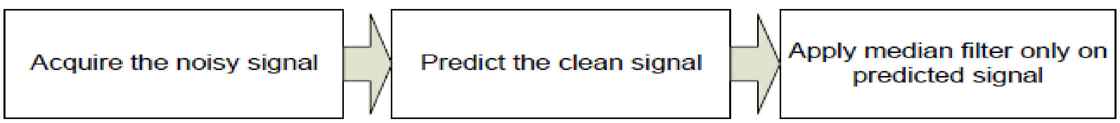


Figure 9: Block diagram of Gaussian noise removal using prediction

So far, we have tested the new algorithms on the signals corrupted by impulse noise and Gaussian. We will extend them to other types of noise in the future.

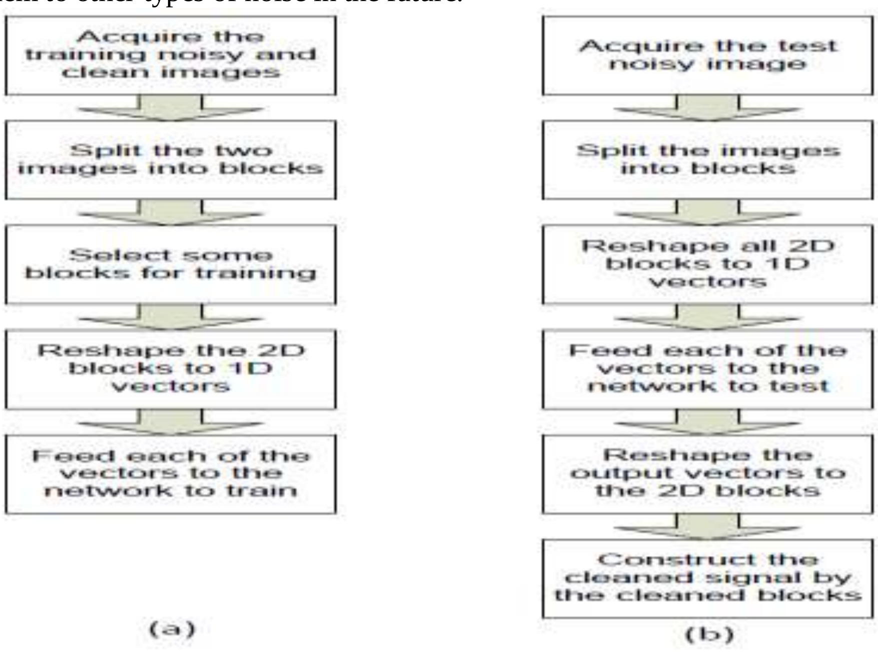


Figure 10: Block diagrams of 2D denoising via prediction; (a) training phase; (b) test phase

2D Noise Removal

In this section, the Neuro-Fuzzy prediction system is used to remove the impulse noise in the 2D signals. The block diagram of the training and test phases are presented in Figure 10. The training phase starts with acquisition of a clean signal and its noisy version. Both images are split into a number of blocks which are subsequently reshaped to 1D vectors. The vectors are fed to the network in order to learn the parameters. Having a trained network, we can continue by predicting the clean copy of new test noisy images. The test images are broken into the blocks with the same size as training blocks. The data blocks are converted to a linear vector and then fed to the network to predict the denoised vector. After cleaning each vector they are reshaped back to the original block sizes. Finally, all the blocks are put together to build a clean image.

The problem with this approach is that the borders between blocks appear after noise removal. This may be alleviated by another Neuro-Fuzzy system which learns what the border means. Another approach is to predict apply the prediction algorithm first on the rows and then on the columns to obtain the clean image. This method will surpass the last one in the sense of eliminating the borders appearing between blocks after prediction.

The proposed approach has shown to considerably increase these two values for all cases.

Using above method requires us to accurately adjust the parameters values of the prediction algorithm. To avoid this restriction we propose to use another technique in which the parameters do not need to be precisely specified but rather by approximately tuned variables the output will be satisfactory.

In the proposed solution, an almost cleaned image is predicted using the Neuro-Fuzzy system. Then the difference image between the noisy and predicted image is generated which can introduce the noise locations. Subsequently, a median filter is only applied on the noise regions proposed by the difference image.

The block diagram of the training and test phase of the proposed algorithm is presented in Figure 11. By the new method we are able to reconstruct the clean image more reliably than when median filter is performed on whole pixels of the image. The zoomed views of the denoised images are compared with median filter 3x3 in Figure 12. The fine features are not smoothed if the new technique is used, while significant amount of details is destroyed by median filter.

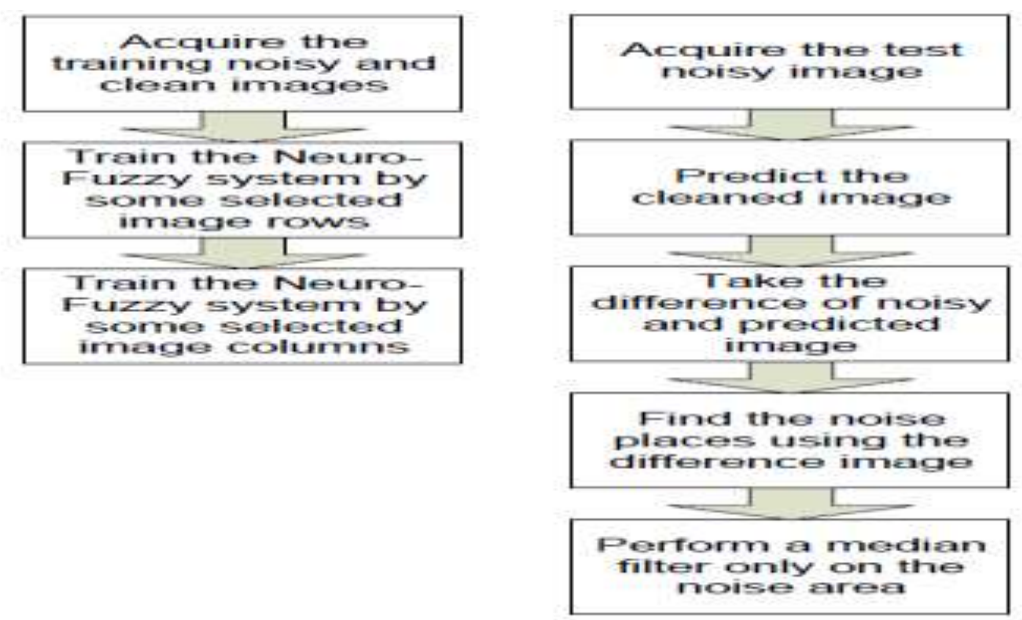


Figure 11: Block diagrams of 2D denoising via prediction using rows and columns and by predicting the noise locations; (a) training phase; (b) test phase

Figure 12: The zoomed view of the clenaed images using denoising by prediction on rows and columns; first row: original image; second row: image corrupted by 0.02 impulse noise; third row: cleaned image using median filter 3x3; fourth row: cleaned image using Neuro-Fuzzy system

Conclusions and Discussions

In this paper, an overview of most common forecasting techniques was presented. Several applications were listed for each method. Among all the applications, electric load forecasting was picked to be used in implementation of the developed algorithms. We also suggested that signal prediction algorithms can be employed to improve the quality of the signal denoising methods. The Neuro-Fuzzy prediction system was used to suppress the impulse and Gaussian noise. To suppress the impulse noise, noise locations were derived first by subtracting the noisy and predicted signals. Subsequently, a median filter of a suitable size was applied only on the corrupted parts of the signal. To remove the Gaussian noise, a mean filter was performed on the resulting predicted signal. The simulation results demonstrated that the RMSE of the filtered signal using the new technique was less than the original filters. The size of the median and mean filters can be adaptively changed based on the noise level in several areas of the signal. The filter size estimation will be accomplished in this study, in the future. For 2D signal (image) denoising we proposed that by finding the locating the noise regions and then applying a median filter on only those areas we are able to achieve a high quality cleaned image compared to when the median filter is performed on whole image. The other application of our prediction algorithm can be reconstructing the missing parts of the fingerprint images.

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