Development of a Method for Wavelet Multispectral Analysis to Weather Forecasting

D.Bullibabu[1], Ch.V.M.S.N.Pavan Kumar[2], Dr.Amit.P.Kesarkar[3]

[1]M.Tech Student, Dept of ECE, Bapatla Engineering College, Bapatla, Andhra Pradesh, India.
[2]Asst.Professor, Dept of ECE, Bapatla Engineering College, Bapatla, Andhra Pradesh, India.
[3]Scientist/Engineer-SE, National Atmospheric Research Laboratory (NARL), Dept of Space, Gadanki, Tirupati, India.

Abstract--The behaviors of many physical processes in the world are governed by multiscale forces. Therefore time series analysis of various observables such as atmospheric temperature, rain fall, pressure or electromagnetic signals in MRI scan, earth's magnetic fields etc shows that multispectral bebavior. This paper will develop method which will help user to perform multispectral analysis of the signals. The objective of this method is to enable user to filter random noise and retain strong as well as weak periodicities of the signal to reconstruct the signal using wavelet filter banks. This method will provide various filter bases such as Haar, Daubechies construct filter banks. After removal of noise from signals this method reconstructs the signal using principal component analysis or spectral fusion techniques. These spectral components will be used as an input to linear prediction models such as autoregressive and moving average model and nonlinear prediction model such as artificial neural network in spectral domain. The predicted spectral components will be reconstructed back in physical space for change detection in future using same wavelet base. We survey a number of applications of the wavelet transform in time series prediction.

Keywords: *Atmospheric Temperature, Wavelet base, Filter banks, Wavelet, Principal component analysis, moving average model.*

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1. INTRODUCTION

There has been abundant interest in wavelet [3] methods for noise removal in 1D signal. In many hundreds of papers published in journals throughout the scientific and engineering disciplines, a wide range of wavelet based tools and ideas have been proposed and studied. Initial efforts included very simple ideas like Thresholding of the orthogonal wavelet coefficients of the noisy data, followed by the reconstruction. Wavelet analysis is originally introduced in order to improve seismic signal analysis by switching from short time Fourier analysis to new better algorithms to detect and analyze abrupt changes in signals Daubechies [1], Mallat [2]. In time-frequency analysis of a signal, the classical Fourier transform analysis is inadequate because Fourier transform of a signal does not contain any local information. This is the major drawback of the Fourier transform. To overcome this drawback, Denis Gabor in 1946, first introduced the short-time Fourier transform. Again in short term Fourier transform there is a time-frequency resolution problem. To overcome this drawback we move to wavelet analysis. The modern applications of wavelet theory as diverse as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics some other medical image technology.

In this paper we propose a new combined prediction and filtering method, which can be seen as a bridge between the wavelet denoising techniques and prediction models. Section I introduces the Haar wavelet transform to eliminate any white noise or other noise present in the Time series data. Section II Describes the Principal component analysis to reduce the data Dimensions. Section III Describes the Moving average model to forecast the future time series data. It can be used either merely for prediction or as the data reduction along with filtering.

1.1. Wavelet Based Weather forecasting system:

In this method the input data is taken from the surface flux tower. It is 10 m height from the ground level. The flux data tower will give the Readings of temperature, wind pressure, Humidity, Simultaneous measurement of CO_2 and H_20 in the free atmosphere and the amount of precipitation or rain fall for each second one reading. At present one day it will display 86,400(24*60*60) records. The input data is nothing but the daily temperature profile readings. At National Atmospheric Research Laboratory (NARL), Gadanki (13.8ºN, 79.2ºE) near Tirupati, India, a surface flux tower system was installed. The input data is applied to the Quality and control block to threshold the temperature readings. That means if any bird sits on the flux data tower sensors or if any extreme atmospheric conditions the temperature readings may cross the limit. So, the quality and control block used to limit the temperature readings from -10^0c to 60^0c.

I. Haar Transform to eliminate the noise:

The continuous wavelet transform of a continuous function produces a continuum of scales as output. However input data are usually discretely sampled, and furthermore a "dyadic" or two fold relationship between resolution scales is both practical and adequate. The latter two issues lead to the discrete wavelet transform. The family of N Haar

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functions $h_k(t)$, (k=0,1,2…..N-1) are defined on the interval $0 \le t \le 1$. The shape of the Haar function [5], of an index k, is determined by two parameters: p and q, where

$$k = 2^P + q - 1 \qquad 1$$

K	0	1	2	3	4	5	6	7	8	9	10
P	0	0	1	1	2	2	2	2	3	3	3
Q	0	1	1	2	1	2	3	4	1	2	3

Table 2.1.Variation of p and q values with index K value

When $k = 0$, the Haar function is defined as a constant $h_0(t) = 1/\sqrt{N}$; when $k > 0$, the Haar function is defined as

$$h_k(t) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \le t < (q-0.5)/2^p \\ -2^{p/2} & (q-0.5)/2^p \le t < q/2^p \\ 0 & \text{otherwise} \end{cases} \qquad 2$$

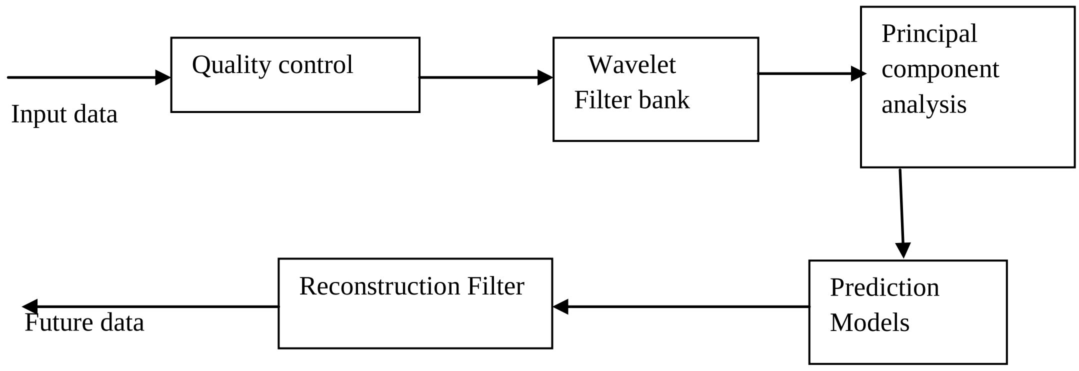

Fig.1: A Wavelet based Weather forecasting system

From the above equation 2, one can see that p determines the amplitude and width of the non-zero part of the function, while q determines the position of the non-zero part of the Haar function.

The N Haar functions [8] can be sampled at t = m/N, where m = 0, 1, 2 ….N-1 to form an N by N matrix for discrete Haar transform for example, when N = 2 , we have

$$H2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The Haar transform $HT^n(f)$ of an N-input function $X^n(f)$ is the 2^n element vector

$$HT^n(f) = \mathbf{H}^n X^n(f) \qquad 3$$

Depending up on the input vector size, we are generating the Haar matrix and multiply with the input vector that is Haar transform. Many filtering methods have been proposed in the last ten years. Here multiplying the input vector with the Haar matrix consists of setting to 0 all wavelet coefficients which have an absolute value lower than a thresholding. After eliminate the noise from the input data we are simply reconstructing the data by using the inverse Haar transform. The Haar transform matrix is real and orthogonal. Thus, the inverse Haar transform can be derived by the following equations.

$H = H^*$ and $H^{-1} = H^T$, So that $HH^T = I$.

So the inverse Haar transform is given by

$$x_n = H^T y_n \qquad 4$$

By the inverse Haar transform, we are reconstructing the input information back. But input data is large dimension in order to reduce the data dimension we go for the principal component analysis.

II. Principal component analysis:

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. The claim that the PCA [4] used for dimensionality reduction preserves most of the information of the data is misleading. Indeed, without any assumption on

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the signal model, PCA cannot help to reduce the amount of information lost during dimensionality reduction [7], where information was measured using Shannon entropy.

Under the assumption that X= s + n, i.e., that the data vector is the sum of the desired information-bearing signal and a noise signal one can show that PCA can be optimal for dimensionality reduction also from an information-theoretic point-of-view.

Principal component analysis algorithm:

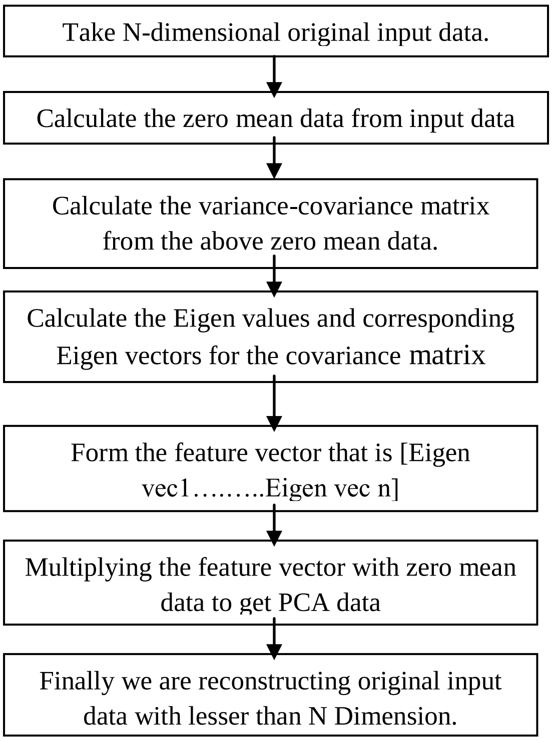

Fig.2: PCA algorithm

III. Moving average model:

Moving average model is used to forecast the future temperatures based on the present and past year temperature data. This method uses the Moving Average [6] formula to average the specified number of periods to project the next period. You should recalculate it often (monthly or at least quarterly) to reflect changing temperature data.

In statistics, a moving average (rolling average or running average) is a calculation to analyze data points by creating a series of averages of different subsets of the full data set. It is also called a moving mean (MM) or rolling mean and is a type of finite impulse response filter. Variations include: simple, and cumulative, or weighted forms. Given a series of numbers and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward"; that is, excluding the first number of the series and including the next number following the original subset in the series. This creates a new subset of numbers, which is averaged. This process is repeated over the entire data series. The plot line connecting all the averages is the moving average. A moving average is a set of numbers, each of which is the average of the corresponding subset of a larger set of datum points. A moving average may also use unequal weights for each datum value in the subset to emphasize particular values in the subset.

A moving average is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The threshold between short term and long-term depends on the application, and the parameters of the moving average will be set accordingly. For example, it is often used in technical analysis of financial data, like stock prices, returns or trading volumes. It is also used in economics to examine gross domestic product, employment or other macroeconomic time series. Mathematically, a moving average is a type of convolution and so it can be viewed as an example of a low-pass filter used in signal processing. When used with non-time series data, a moving average filters higher frequency components without any specific connection to time, although typically some kind of ordering is implied. Viewed simplistically it can be regarded as smoothing the data.

In Many applications a simple moving average (SMA) is the unweighted mean of the previous N data. However, in science and engineering the mean is normally taken from an equal number of data on either side of a central value. This ensures that variations in the mean are aligned with the variations in the data rather than being shifted in time. An example of a simple equally weighted running mean for a n-day sample of temperatures is the mean of the previous n days' closing temperatures. If those temperatures are TM, TM-1, TM-(N-1) then the formula is

$$SMA = \frac{P_M + P_{M-1} + P_{M-(N-1)}}{N} \qquad 5$$

When calculating successive values, a new value comes into the sum and an old value drops out, meaning a full summation each time is unnecessary for this simple case, The period selected depends on the type of movement of interest, such as short, intermediate, or long-term .

IV. Results:

In this model, the input data is temperature readings that are taken from the surface flux tower. The input data is taken from the June month of the year 2014.The time versus temperature plot for the 1st day of June month is shown in figure3.These temperature readings are applied to wavelet

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filter bank to eliminate the noise present in the data. After removing the noise from the data it is applied to PCA to reduce the dimensionality. Later this data is applied to Moving average model to predict the future temperatures that is July month temperatures of the year 2014.

The time versus temperature plot for the July month of the 1st day is shown in figure 4.

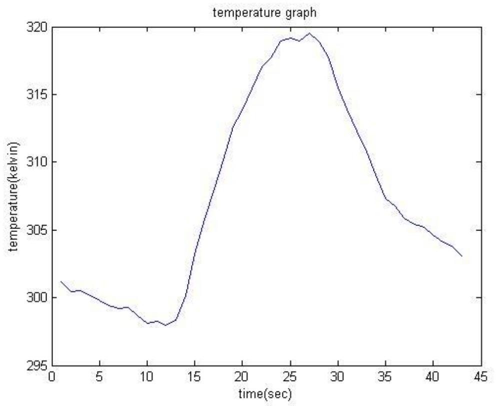

Fig.3: the time versus temperature plot for June month 1st day of 2014.

Now, we are comparing the predicted July month temperatures with the original June month temperature that are shown in figure 4.

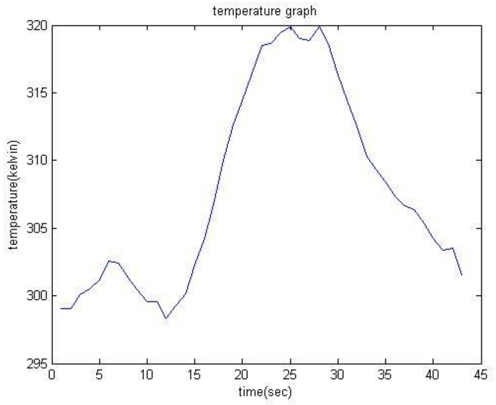

Fig.4:time versus temperature plot for July month 1st day of 2014.

Later we compared the June month temperatures with July month temperatures there is a small decrement change in temperatures that are shown in figure 5.

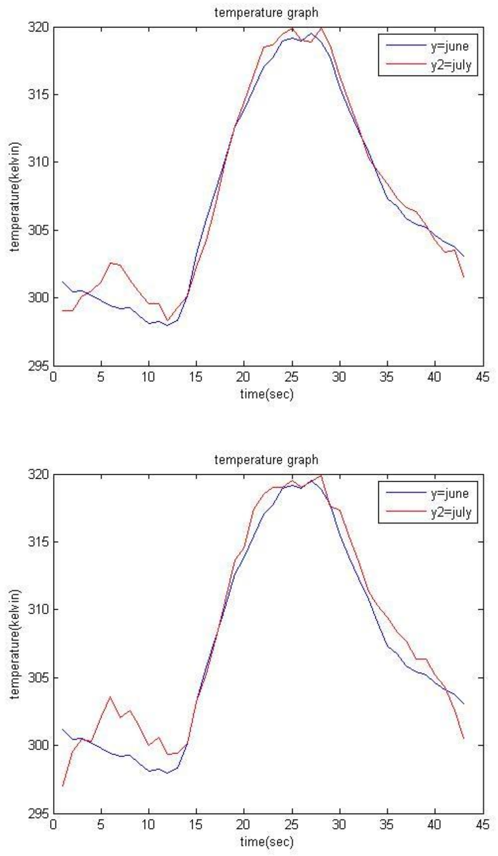

Fig.5:Temperature comparison plots for June and July 1st and 2nd days for 2014.

From this model we conclude that the July month temperatures are little variation compared to June month temperatures.

V. Conclusion

We have presented in this article a new and simple method for the prediction of time series and filtering process that are measured with noise. It is based on a simple Haar transform of the time series data to eliminate the noise. We go for the PCA to reduce the dimensionality present in the data. In the case of prediction, virtually any prediction scheme can be adapted to the multi-resolution representation induced by the transformation, but even with the simplest scheme of all, the moving average model, this method is able to capture short and long term memory components in an adaptive and very efficient way .Java code has been implemented successfully for this model and to estimate the future atmospheric data based on the past data.

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