

# *A Method for Correcting Synchronization Error using Wavelet Transformation*

Shweta Srivastava  
Electronics & Communication,  
BBDU, Lucknow, India  
[shweta.srivastava0319@gmail.com](mailto:shweta.srivastava0319@gmail.com)

Pallavi Gupta  
Electronics & Communication Department,  
BBDU, Lucknow, India  
[pallavi.gupta1606@yahoo.com](mailto:pallavi.gupta1606@yahoo.com)

**Abstract--** Sensor network conventions have a one of a kind self-sorting out capacity with interesting component of WSNs of the sensor nodes collaboration with each other. Sensor hubs have an in-assembled processor, utilizing which raw data are handled before transmission. These components encourage extensive variety of uses of WSNs extending from biomedical, natural, military, occasion recognition and vehicular telematics. These days, modern applications are based on conveyed structures and they are required to be economical, adaptable and tried and true. The framework's execution can be enhanced by interfacing sensors and actuators straightforwardly to the mechanical correspondence system, as information and diagnostics can be made available to numerous frameworks furthermore shared on the web. This paper introduces a survey of the examination issues in the uses of Wireless Sensor Networks. Accuracy in WSN cause different type of problem in message exchange between nodes. The message is disordered, lost due to accuracy which is minimizes or reduces by the help of synchronization protocol. Some application requires that a message must be delivered within a specific time, otherwise the message becomes useless or its information content decrease after the time bound. Therefore one of the main goals of these protocols is to completely control the network delay. The goal of this research in WSN is to improve the accuracy by minimizing error due to loss of synchronization or delay in synchronization. In this research we reconstruct the signal and developed an approach to recover the true signal and different approaches based on synchronization are proposed for optimal functionality.

**Keywords:** Synchronization, Cross Power Spectral Density, FFT, WSN, Wavelet Transformation.

## I. INTRODUCTION

A Wireless Sensor Network (WSN) is a group of hundreds or thousands of sensor nodes that have capabilities of sensing the environment and communicate the information in wireless medium [1]. Wireless sensor network is the collection of sensor nodes with limited resources that work jointly in order to achieve a common goal. Sensor nodes are not only used for military applications, and they have also used in geographical monitoring, environmental monitoring and control, pollution monitoring, target tracking, navigation, transport, health and medical, emotion based computing and so on. The limited energy resource is

the drawback of the wireless sensor networks, so to save the energy, the nodes must turn on and off their transceiver at appropriate time, an accurate timing between the nodes is required. Sensor nodes are very tiny device and running with a limited energy, so it is not simple to synchronize nodes effectively because an energy consumption.

There are lots of reasons to showing the synchronization problems in sensor networks. Some reasons are as following:

1. Sensor nodes are required to co-ordinate their operations to perform a special task, e.g. Data fusion. In this data is collected at different nodes or a single node are combined into a meaningful result.
2. Life time of network is dependent on the power. So to increase the life of network, we need to used power saving methods. Example, when using power-saving modes, the nodes must be sleep and wake up at coordinated times means synchronized.

Time synchronization is important for a sensor network. Time synchronization in a network is for providing a common time for nodes in the network. To recognize the correct event time, sensor nodes must be synchronized among themselves with universal time called global time. Therefore, time synchronization is significant characteristics in Wireless sensor networks. Local clock make time synchronization an important part of WSN.

Four basic components of time synchronization which provide communication delay [5]:

- Send Time
- Access Time
- Propagation Time
- Receive Time

### **Send Time**

Send time which is the total time of building the message and transfer it to the network interface to be sent. This time mostly depends on the operating systems in use.

### **Access Time**

Access time is that time in which the time needed to access the channel. Every network engages a medium access control scheme.

### **Propagation Time**

Propagation time is that time in which the time required to propagating the message through the air from the network interface of the sender to the network interface of the receiver.

### Receive Time

Receive time is that time in which the time spent by the receiving node in receiving the message by network interface and transmitting it to the application layer of the host and decode it.

The performance of time synchronization is effected by various factors such as Precision, Complexity, Convergence time, Network size, and Energy consumption.

## II. RELATED WORK

If partners derive utility from joint leisure time, it is expected that they will coordinate their work schedules in order to increase the amount of joint leisure. In order to control for differences in constraints and selection effects, this work uses a new matching procedure, providing answers to the following questions: (1) Do partners coordinate their work schedules and does this result in work time synchronization?; (2) which partners synchronize more work hours?; and (3) is there a preference for togetherness?

**Chris van Klaveren, and Henriette Maassen van den Brink, (2007) [1]**, found that coordination results in more synchronized work hours. The presence of children in the household is the main cause why some partners synchronize their work times less than other partners. Finally, partners coordinate their work schedules in order to have more joint leisure time, which is evidence for togetherness preferences.

In [2] recent years there has been a growing interest in Wireless Sensor Networks (WSN). Recent advancements in the field of sensing, computing and communications have attracted research efforts and huge investments from various quarters in the field of WSN. Also sensing networks will reveal previously unobserved phenomena. The various areas where major research activities going on in the field of WSN are deployment, localization, synchronization, data aggregation, dissemination, database querying, architecture, middleware, security, designing less power consuming devices, abstractions and higher level algorithms for sensor specific issues. This work provides an overview of ongoing research activities, various design issues involved and possible solutions incorporating these issues. This work provided a cursory look at each and every topic in WSN and our main aim is to introduce a newbie to the field of WSN and make him understand the various topics of interest available for research. Wireless Sensor Networks have created wide range of challenges that still needs to be addressed. In this work **Gowrishankar. S, T. G. Basavaraju, Manjaiah D. H, and Subir Kumar Sarkar, (2008), [2]**, have identified a comprehensive list of issues associated with Wireless Sensor Networks. They have also discussed some popular protocols implementing these issues in part or as a whole. The impact of wireless sensor networks on our day to day life can be preferably compared to what Internet has done to us. This field is surely going to give us tremendous opportunity to change the way we perceive the world today.

Modal parameters identification with emphasis on the natural frequencies and mode shapes of the 5-storey steel structure based on both FDD and WT has been presented in

comparisons between them as well as with FE model results by **Thai-Hoa Le and Yukio Tamura, (2008) [3]**. Identified natural frequencies and mode shapes from FDD and WT are quite good agreement with the FE results. It seems that FDD expresses better than WT in the natural frequencies extraction not the low-order modes but also high-order ones. FDD can extract natural frequencies at arbitrary frequency resolution, where WT is favorable for actually dominant frequencies. WT also requires more localized high-resolution analysis for extracting natural frequencies of high-order and non dominant mode shapes.

The effect of non-synchronous sensing when using wireless sensors on structural modal identification is addressed and a methodology for correcting such errors proposed by **Z.Q. Feng, and L.S. Katafygiotis (2011) [4]**. Their work first discussed the potential sources causing non-synchronous sensing and estimates the extent of non-synchronous sensing based on data collected from Imote2 sensors, and then investigated the impact of synchronization errors in the measured output response on modal identification using numerical simulations. The simulation results show that even small synchronization errors in the output response can distort the identified mode shapes. A new methodology is proposed herein for eliminating such errors. This methodology estimates the power spectral densities (PSDs) of output responses using non-synchronous samples directly based on a modified FFT. As long as the corrected PSDs are obtained, the correlation functions can also be easily obtained by IFFT. Then these corrected PSDs or correlation functions can be fed into various output only modal identification algorithms. The proposed methodology is validated using numerical simulations. It is found that the simulation results closely match the identified parameters based on synchronous data.

Considering its central importance to sensor networks, time synchronization has received extensive attention by the research community. Nevertheless, **Yin Cheny Qiang, Wangz, Marcus Changy and Andreas Terzis, (2011) [5]**, argue in this work that existing approaches introduce undesirable trade-offs. For example, while GPS offers excellent accuracy for outdoor deployments, the high cost and power consumption of GPS receivers make them prohibitive to many applications. Message-passing protocols, such as FTSP, introduce different sets of compromises and constraints. In this work, we present an inexpensive and ultra-low power ( $< 100 \mu\text{A}$ ) mote peripheral, we term the Universal Time Signal Receiver, that leverages the availability of time signals transmitted by dedicated radio stations around the globe to provide access to UTC time with millisecond-level accuracy. We present experimental results measuring signal availability, quality of synchronization across motes, and power consumption. We show that the proposed universal time signal receiver achieves global time synchronization and for applications where millisecond-level precision is sufficient, it consumes up to 1,000 times less energy than GPS or FTSP.

### III. METHODOLOGY

In order to eliminate the synchronization errors, direct intuition suggests reconstructing the synchronous samples from measured non-synchronous ones. This is so called signal reconstruction, and some work has been done for this purpose. Rather than reconstructing the signal in the time domain, we develop a correction approach to recover the true spectral density using non-synchronous samples in the frequency domain. This approach is based on the spectral relationship of synchronous data and non-synchronous data. Because only spectral densities or correlation functions are needed for most of modal identification algorithms and raw synchronous time histories are not needed, reconstruction of the signal in the time domain is unnecessary. As long as we are able to obtain the corrected spectral densities, the correlation functions can also be easily obtained by IFFT and then we apply DWT and improve it.

#### Constant time shift

Consider two time histories  $\{x_\alpha(0), x_\alpha(\Delta t) \dots\}$  and  $\{x'_\beta(\delta), x'_\beta(\Delta t + \delta), \dots\}$

Where  $\delta$ =constant time shift in  $x'_\beta$

Calculate the discrete Fourier transform (DFT) for  $x_\alpha$

$$X_\alpha(\omega_k) = \sum_{n=0}^{N-1} x_\alpha(n\Delta t) e^{-j\omega_k n\Delta t} \quad (1)$$

Where  $\omega_k = k\Delta\omega$

Now we have to calculate the DFT of the shifted signal  $x'_\beta$

$$X'_\beta(\omega_k) = e^{j\omega_k \delta} \cdot X_\beta(\omega_k) \quad (2)$$

Here  $X_\beta(\omega_k)$  is the DFT of the original signal.

Therefore,

$$X_\beta(\omega_k) = X'_\beta(\omega_k) e^{-j\omega_k \delta} \quad (3)$$

Where  $w_k = k\Delta w$

Then, the true cross spectral density estimate can be obtained by:

$$S_{x_\alpha x_\beta}(w_k) = \frac{\Delta t}{N_\alpha} E[X_\alpha(w_k) X'_\beta(w_k)] \quad (4)$$

#### Linear time shift

Consider two time histories  $\{x_\alpha(0), x_\alpha(\Delta t_\alpha) \dots\}$  and  $\{x_\beta(0), x_\beta(\Delta t_\beta) \dots\}$

Having different sampling frequencies, i.e.

$$\Delta t_\alpha \neq \Delta t_\beta$$

In order to ensure that  $X_\alpha(w_k)$  and  $X_\beta(w_k)$  correspond to the same discrete frequency when calculating the cross spectral density, their frequency resolutions should be identical, i.e.

$$\Delta\omega_\alpha \equiv \Delta\omega_\beta$$

So there duration time should be same i.e.,

$$N_\alpha \Delta t_\alpha = N_\beta \Delta t_\beta$$

$$\frac{N_\alpha}{N_\beta} = \frac{\Delta t_\beta}{\Delta t_\alpha} \quad (5)$$

Where  $\Delta t_\alpha$  =Sampling Interval  $\Delta t_\beta$ =Sampling Interval

So the cross spectral density:

$$S_{x_\alpha x_\beta}(w_k) = \frac{\Delta t_\alpha}{N_\alpha} E[X_\alpha(w_k) X'_\beta(w_k)] = \frac{\Delta t_\beta}{N_\alpha} E[X_\alpha(w_k) X'_\beta(w_k)] \quad (6)$$

In reality, the time shifts of **non-synchronous data** are a combination of constant time shifts and linear time shifts [4].

#### A. Algorithm

The procedures for computing the true power spectral density estimate from non-synchronous data in WSN are as follows:

Step 1: Calibrate the sampling frequencies of each sensor board before sensing experiment.

Step 2: Do sensing experiment, and make sure the time stamps are also recorded when sampling.

Step 3: Set one sensor as reference and partition the data into several segments. Each segment has a length of  $Nr$  data points.

Step 4: Partition the data in other sensors into several segments as well. The first data point of each segment is chosen as close as possible to the first data point of the corresponding segment in the reference sensor data by comparing their time stamps. The length  $Ni$  of each segment is chosen such that the Eq. (5) holds approximately.

Step 5: Calculate the wavelet transform of each segment and perform denosing.

Step 6: Calculate the cross spectral using Welch method.

Step 7: Apply peak finding algorithm and determine the peak values of CPSD spectrum and the respective frequencies at 5 significant peaks.

#### B. System parameters

TABLE I. SYSTEM PARAMETERS

Sensing instant	10000
Sampling Frequency (fs)	40Hz
Sampling Time (Ts)	0.024 sec
Sampling Instant	k.Ts
Number of Node	2

C. Flowchart

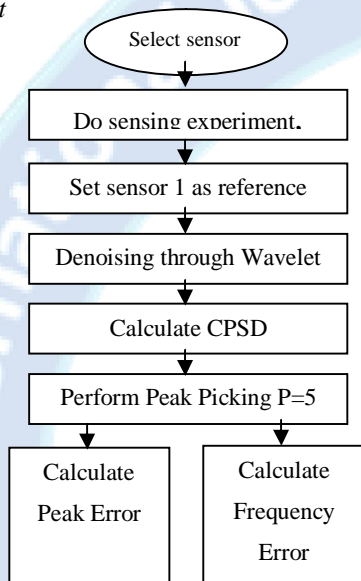


Fig 1: Flow chart

IV. RESULT AND DISCUSSION

the analysis of non-synchronous sensor behavior and modal identification is performed by using MATLAB programming environment simulations. A new wavelet denoising based cross power spectral density estimation for eliminating synchronization errors is described and validated by an illustrative example using simulated data. The potential sources behind non-synchronous sensing considered in this work are clock synchronization error; non-simultaneous sensing start-up time, differences in sampling frequency of the sensor nodes and non-uniform sampling interval with respect to the time. All the signal is sampled with a constant sampling interval of  $T_s$  and all the sensors are simulated to start sensing at the similar time. Due to the reasons mentioned above, the  $k^{th}$  data point is actually sampled at a different time instant:

$$tk' = k.T_s + \delta + ck + \epsilon(k)$$

where,  $\delta$  : constant time shift, coming from sources since the clock synchronization error is relatively very low hence in this case sensing start-up time delay is considered only.

ck: linear time shift, coming from source the coefficient c is the difference in the real sampling time and nominal sampling time.

$\epsilon(k)$  : random time shift, these time jitters result in a error type of non-uniform sampling.

As per the above parameter definitions the values which are specified in the algorithm are:

Sampling time (sec) ;  $T_s = 0.025$

No. of sensors;  $N = 15$

b) Sensors startup time error; del (secs.) = [ -0.0017266 - 0.00025469 -0.0013046 -0.0018956 0.0018187 - 0.00027761 0.0018462 0.0010497 -0.0019706 0.00072015 0.0008238 0.00058052 0.00020924 - 0.0011276 0.0010895].

c) difference in sampling frequency:

for baseline it is no shift ;  $c1=0$ ,

for constant shift (sec)  $c2 = 0.02$  seconds and for linear shift (sec)

$fs1 = 40.486$  hertz

$fs2 = 39.84$  hertz

$Ts1 = 0.0247$  secs.

$Ts2 = 0.0251$ secs

$c3$  (sec.) = [ 0.00029998 0.00029998 -0.00010021 - 0.00010021 0.00029998 0.00029998 -0.00010021 - 0.00010021 -0.00010021 -0.00010021 0.00029998 - 0.00010021 0.00029998 -0.00010021 0.00029998].

we have applied 1-D wavelet denoising on the received signal on all the segments and then evaluated the CPSD of X1 and X2 segments to determine the peak values of spectrums and the frequency values at respective peaks.

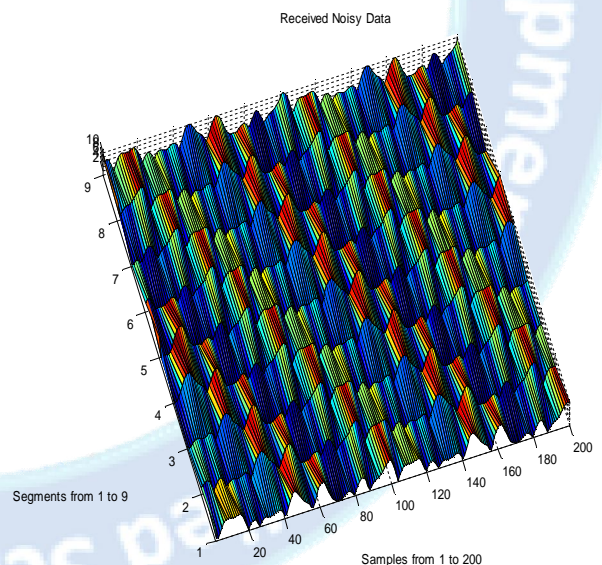
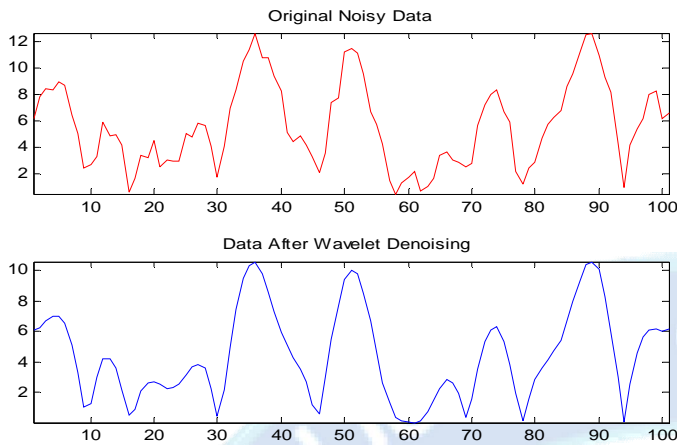
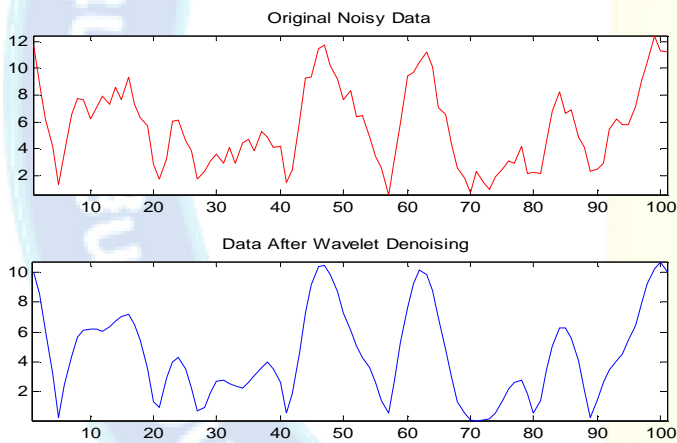


Fig 2: Segment wise Wavelet Transform at different sampling instants.



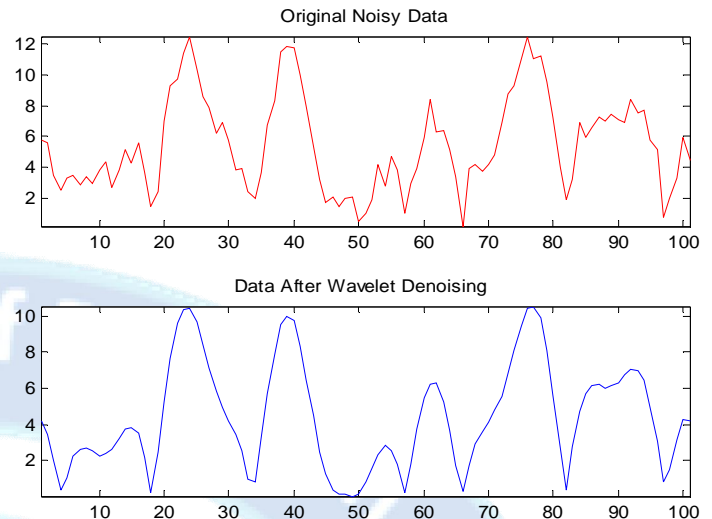
**Fig 3a. Data before and after 1D DWT denoising for segment 1.**

The data segments are passed through the wavelet transforms and the wavelet decompositions produced the segment data in different components such that the signal is decomposed into several frequency component. The high frequency components are suppressed and thus the signal flickers related distortions are eliminated. Figure 1 shows the data obtained after DWT of noisy segments. These are 1 to 9 segments and each segment has 200 samples. Hence the transformed data is shown in surface plot.



**Fig 3b: Data before and after 1D DWT denoising for segment 2.**

After applying the wavelet denoising the CPSD in between segments of X1 and X2 received signal is evaluated by Welch method. The peak finding command is used for determining the cross power spectrum magnitude and the respective frequency index and the frequencies are determined for both data i.e peak finding data of signal; without applying 1-D DWT denoising and with applying denoising.



**Fig 3c: Data before and after 1D DWT denoising for segment 3.**

## V. CONCLUSION

The purpose of this work is to implement an algorithm using MATLAB platform for analyzing and removing the challenges of non-synchronous sensing errors in the sensor nodes using modal identification methods in applications of wireless sensor networks. The causes behind the non-synchronous sensing in terms of baseline, constant shift and linear shift are first discussed and then simulated for group of sensors with delay in their sampling time. The effects of this delay are observed and after these there effects on frequency and peak spectrum are estimated based on data collection by the sensors. Among this error behind non synchronous behavior the most prominent ones are non simultaneous activity of sensing at starting and differences in sampling frequency among the entire sensor. According to simulations results of the algorithm it has been concluded that these errors can distort the identified results and hence creates misleading measurements of frequency and spectrum modal shape. A new methodology as a combination of 1D wavelet denoising and Welch power estimation is proposed and implanted by the algorithm for eliminating errors due to loss of synchronization in sensor at sampling time. This methodology selects the signal segments at the point of nearest sampling time error. Then it applies 1D dwt denoising on the received segments and estimates the cross power spectral density (PSD) of output responses of pair of sensors generated segments using non-synchronous samples and applies Welch method of spectrum estimation based on a FFT. Using this algorithm the corrected cross spectral density is obtained that represents the correlation functions in the IFFT formulation. Thus the corrected CPSDs are frequency domain representative of correlation functions and applied for various applications in future work as an corrected output for modal identification and frequency estimation and pattern recognition algorithms. Comparing with normal methods of peak finding only using CPSD without denoising existing algorithm of raw synchronous time history estimation approach is simple, more accurate and computationally efficient. The proposed methodology is



validated programming simulations. The simulation results match with the frequency and significant peak like parameters based on synchronous data.

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