ENERGY EFFICIENT ADAPTIVE ALGORITHMS FOR WIRELESS SENSOR NETWOKS

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ABSTRACT: In Wireless Sensor Networks (WSNs) as sensor nodes are generally battery-powered devices, the critical aspects to face concern are how to reduce the energy depletion of nodes, so that the network lifespan can be prolonged for a reasonable period. Thus Energy conservation techniques for sensor networks typically rely on the assumption that data sensing and processing consume considerable less energy than communication but this assumption does not hold in all practical application scenarios. In this paper a new improved adaptive algorithm is presented that reduces the energy consumption at node level for data acquisition and communication subsystems of a wireless sensor node. The developed algorithm uses persistent measurements of the signal frequency content as the basis for altering the sampling rate. It is validated that the method eases a substantial decrease in the energy spent in data acquisition and communication, with only marginal loss in signal fidelity.

I. Introduction:

The power of wireless sensor networks lies in the ability to deploy large numbers of tiny nodes that assemble and configure themselves. Wireless sensor networks have the ability to dynamically adapt to changing environments. Adaptation mechanisms can respond to changes in network topologies or can cause the network to shift between drastically different modes of operation. Energy conservation techniques for wireless sensor networks generally assume that data acquisition and processing have energy consumption significantly lower than that of communication. Unfortunately, this assumption does not hold in a number of practical applications, where sensors may consume even more energy than the radio. In this context, effective energy management should include policies for an efficient utilization of the sensors, which become one of the main components affecting the network lifetime.

Data transmission is very expensive in comparison to processing in terms of energy consumption. The energy cost of transmitting a single bit of information is approximately the same as that needed for processing a thousand operations in a typical sensor node. The energy consumption of the sensing subsystem depends on the specific sensor type. Energy consumed by the processing is negligible; data sensing energy expenditure is greater than, the energy needed for data transmission. In general, energy-saving techniques focus on two subsystems. Primarily on networking subsystems where, energy management is taken into account for single node and also in the design of networking protocols. Secondly, on the sensing subsystem here techniques are used to reduce the amount or frequency of energy-expensive samples.

The lifetime of a sensor network can be extended by jointly applying different techniques for energy efficient protocols to minimizing the energy consumption during network activities. The Power management schemes are applied for switching off node components that are not temporarily needed, as large amount of energy is consumed by node components (CPU, radio, etc.) even if they are idle.

Reducing communications may be not enough, but energy conservation schemes have to actually reduce the number of acquisitions (i.e. data samples). It should also be pointed out that energy-efficient data acquisition techniques are not exclusively aimed at reducing the energy consumption of the sensing subsystem. By reducing the data sampled by source nodes, they decrease the number of communications as well. Actually, many energy-efficient data-acquisition techniques have been conceived for minimizing the radio energy consumption, under the assumption that the sensor consumption is negligible.

Since the measured samples may be correlated, the adaptive sampling techniques exploit such similarities to reduce the amount of data to be acquired from the transducer. For example, the temporal correlations can be exploited to reduce the number of acquisitions in case the observed data is varying slowly with time. In case data does not change sharply between areas covered by neighboring nodes the spatial correlations may be exploited.

Given a set of network and environment characteristics and definitions, resource consumption (energy and network bandwidth) should be minimized while maximizing the measurement accuracy. The major concern is to produce a precise spatial picture of a certain physical process, while making an efficient use of resources as events are not uniformly distributed in the environment, not all sensor nodes should collect data samples at a common, fixed rate.

In fixed rate sampling, the rate is same for both high and low frequency components. The energy utilization can be achieved by continuously adjusting the sampling rate in data acquisition to capture dominant features in the signal being acquired. The sampling rate can be increased or decreased depending on the existence of high or low frequency component in a given signal. The Adaptive Sampling Algorithm identifies the minimal sampling frequency guaranteeing reconstruction of the sampled signal and reduces the power consumption of the network by adapting the sample rate to the real needs of the physical phenomena under observation.

Motivation: The frequency display, using standard spectral analysis methods, is useful for the process of stationary signal classification; transient signals (non-stationary signal) are not well matched to these methods. Fourier-based methods are ideally suited for the extraction of narrow band signals whose duration exceeds the Fourier analysis window length. The Short Term Fourier Transform with its non-varying window is not readily adaptable for capturing signal specific characteristics. Moreover, all time resolution is lost within each window. Hence, the Wavelet Packet Transform (WPT) is used for more freedom in dealing with this time-frequency trade-off.

Contribution: The proposed work aims at selecting a suitable sampling rate in accordance with the signal frequency spectral content all through the acquisition process. The likely highest frequency existing in the signal during each consecutive T_H intervals is used to alter the sampling rate for next interval T_L. A wavelet packet based method is used to select and calculate wavelet coefficients, improving efficiency in achieving net energy savings.

Organization: The rest of the paper is organized as follows: In section 2 the literatures of various dynamic schemes to improve network energy saving are discussed. Section 3 describes the data acquisition model assumed. The proposed method for selecting a suitable sampling rate is presented in section 4. Section 5 comprises results and analysis. The finishing remarks are specified in Section 6.

II. Literature Survey:

Several adaptive sampling approaches in different realistic closed control loop scenarios for building automation is compared by Joern Ploennigs et al., [1]. Tradeoff between energy efficiency and reaction latency is being addressed. The adaptive sampling algorithms are compared against common periodic sampling that samples a continuous signal. A rendezvous-based data collection approach is proposed by Guoliang Xing et al., [2] in which a subset of nodes serves as the rendezvous points that buffer and aggregate data originated from sources and transfer to the base station when it arrives. The approach combines the advantages of controlled mobility and in-network data caching and can achieve a desirable balance between network energy saving and data collection delay. In-network compression techniques without centralized coordination to extend lifetime is discussed in [3]. The approach is fully distributed wherein each node autonomously takes a decision about the compression and forwarding scheme to minimize the number of packets to transmit. Pack and Forward (PF) is an energy-safe strategy in which each node tries to encapsulate data in the most efficient way, minimizing the number of outbound packets.

Masoum et al., [4] exploits a dynamic scheme based on how frequent, pattern of sensed data changes instead of using a fixed frequency interval for sensing and data transmission. Cooperative adaptive sampling mechanism based on the award and punishment concept has been proposed to motivate sensor nodes to cooperate with each other. An Adaptive Staggered sLEEp Protocol (ASLEEP) for efficient power management in wireless sensor networks targeted to periodic data acquisition is suggested by G. Anastasi et al., [5]. This protocol dynamically adjusts the sleep schedules of nodes to match the network demands, even in time-varying operating conditions. Hamouda et al., [6] discuses a distributed multi-sensor multi-target tracking scheme for energy-efficient MTT with adaptive sampling. Behavioral data obtained while tracking the target including the target's previous locations are recorded as metadata to compute the sampling interval so that the tracking continuity and energy efficiency are improved. Gupta et al., [7] presented the adaptive sampling technique called Exponential Double Smoothing-based Adaptive Sampling (EDSAS), in which the temporal data correlations provide an indication of the prevailing environmental conditions and are used to adapt the sensing rate of a sensor node. EDSAS uses irregular data series prediction to reduce sampling rate in combination with change detection to maintain data fidelity.

Xiang-Yang Li et al., [8] proposed a novel adaptive sampling and diversity reception approach that can significantly reduce the energy consumption of network while maintaining high accuracy of audio stream. By selectively picking sampling nodes and adaptively adjusting their sampling rates, sufficient samples arrive at the fusion node for high recovering fidelity. Tommy Szalapski et al., [9] proposed assistance based adaptive sampling algorithm. When a sensor requires a higher sampling rate then it has currently been allocated, it listens to its neighbors' transmissions and sends a request for assistance from neighbor. By this method high bandwidth utilization while minimizing the amount of extra traffic introduced in the system. Yousef et al., [10] have selected the sampling rate based on previous metadata (history). Hence achieve better energy consumption by reducing the number of sampling instants. Jain et al., [11] proposed a decentralized approach to adaptive sampling which uses a Kalman filter to predict the sensor node activity and adjust the sampling frequency correspondingly.

Irfan Ahmed et al., [12] presented an adaptive rate communication in conjunction with cooperative MIMO for uniform energy load distribution in wireless sensor networks (WSN). The inherent data flow structure of WSN causes uneven load distribution in the network. S.M. Mahmud [13] suggested an adaptive sampling technique for measuring the difference in phase between the fundamental components of two signals: the sampling rate is increased until the phase is correctly measured or the sampling rate reaches the maximum sampling rate of the system. Spatial correlation [14] is used, in the back casting scheme. The main idea is that, nodes deployed with sufficient density do not have to sample the sensed field in a uniform way. More nodes have to be active in the regions where the variation of the sensed quantity is high. In a given area, the process of activating the desired number of sensor can be done in two phases. In the first phase, called preview, only a subset of nodes are activated for sensing. Based on this initial estimation, in the second phase called refinement, the fusion center can activate additional sensors in the locations when the spatial correlation is low.

Background Work: The temporal analysis of sensed data is used to propose an adaptive sampling scheme suitable to snow monitoring for avalanche forecast [15]. A periodically sampled parameter – i.e. the snow equivalent capacity is used to derive the actual signal. From the Nyquist theorem it is known that the sampling frequency needed for the correct reconstruction of the original signal should be $F_s \geq 2 \times MF$ where MF is the maximum frequency in the power spectrum of the considered signal. The algorithm relies on a modified CUSUM test to set the sampling rate. As computations are heavy, a centralized approach is taken, i.e. the algorithm is executed at the sink for each sensor node. The estimated sampling rates obtained by the sink are then notified to sensor nodes. A. R. Varkonyi-Koczy et al., [16] describes a Fourier analyzer which autonomously adapts the parameters of the filters to match the signal components and the measuring channels. The result is that the picket-fence effect and leakages are reduced but the method can be applied only to periodic signals.

Problem Formulation: The events are not uniformly distributed in the environment, not all sensor nodes should collect data samples at a common fixed rate. Hence Adaptive Sampling Algorithm identifies the nominal sampling frequency ensuring reconstruction of the sampled signal and reduces the power consumption of the network by adjusting the sample rate to the real needs of the physical phenomena under observation. Environments are often extremely dynamic and therefore sensors are needed to continuously alter to dynamic systems. This can only be achieved if the physical phenomenon is sensed or sampled from the environment at a precise rate.

III. Model for Data Acquisition:

Energy-Efficient Data Acquisition Techniques aim at reducing the number of acquisitions (i.e. data samples).The minimized acquirements of the source node decrease the number of communications. The measured samples can be correlated; adaptive sampling techniques exploit such likenesses to reduce the amount of data to be acquired from the transducer. For example, the data under observation may change slowly with time. In this case, temporal correlations (i.e. the fact that subsequent samples do not differ very much between each other) may be exploited to reduce the number of acquisitions. An analogous approach can be applied when the investigated phenomenon does not change sharply between areas covered by neighboring nodes. In this case, energy due to sampling (and communication) can be reduced by taking advantage from spatial correlations between sensed data. Clearly, both temporal and spatial correlations may be jointly exploited to further reduce the amount of data to be acquired. As opposed to fixed rate sampling, the adaptive sampling algorithm varies the sampling rate during the signal acquisition process according to the incoming signal's frequency content. While precise knowledge of a signal's frequency information before the acquisition is not available, an estimate of the current system state can be made based on previously acquired samples.

A. Objective:

Use of wavelet scheme to detect and classify signals possessing non-stationary information.

To estimate the frequency spectrum and highest dominant frequency component *MF*.

To increase the sampling rate when high-frequency terms are incorporated into the wavelet estimator, and decrease it when, signal complexity is judged to have decreased.

To reduce the energy expended in data acquisition and communication.

B. Assumptions:

The received signal is sampled in *i* separate intervals; it can be varied in length and the sampling rate.

Use high sampling rate (HSR) for a sub-interval of length T_H and adjusted sampling rate (ASR) for the remaining interval of length T_L.

IV Algorithms:

The algorithm for sampling rate selection is shown in Table 1 that runs at the node level. Initially a signal with high dynamics such as acoustic, seismic or machine condition monitoring is considered. These signals are passed through a wavelet estimator that computes the wavelet coefficients.

Table 1: Algorithm for Sampling Rate Selection

Step1	Compute the wavelet coefficients for the acquired signal
Step2	Differentiate the coefficients of high and low frequency components.
Step3	Check if the coefficients are greater than threshold (λ= $\sigma\sqrt{2logN}$). If *Yes* Store the coefficients respectively If *No* Set the coefficients to zero
Step4	Apply Additive Increase Additive Decrease algorithm to compute T_L
Step5	Calculate the appropriate sampling rate based on the maximum contributing sub-band (MSB) currently available.
Step6	Repeat Step 2-5 for the depth of decomposition levels considered.
Step7	Reconstruct the signal and calculate energy

A. Wavelet Packet Decomposition:

The Wavelet Packet Decomposition (WPD) of a signal is a step by step transformation of the signal from the time domain to the frequency domain. The top level of the WPD is the time representation of the signal. The trade-off between time and frequency resolution increases as each level of decomposition is calculated. The bottom level of a fully decomposed signal is the frequency representation.

Let *h (n)* and *g (n)* be the finite impulse response low pass and high pass filters used for the decomposition. Let F_0 and F_1 be the operators which perform the convolution of *x (n)* with *h (n)* and *g (n)*, respectively, followed by decimation by two. For example, let $x_s[n]$ and $x_d[n]$ denote the sequences resulting from the low pass filter-decimation operation and high pass filter-decimation, respectively. We have,

$$x_s[n] = F_0\{x(k)\} = \sum_k x(k)h(2n-1) \tag{1}$$

$$x_d[n] = F_1\{x(k)\} = \sum_k x(k)g(2n-1) \tag{2}$$

Due to the decimation, $x_s[n]$ and $x_d[n]$ each contain half as many samples as *x (n)*. Here *s* and *d* notation are used because the low pass F_0 operation may be compared to a sum and the high pass F_1 operation may be compared to a difference.

B. Sampling Rate Selection Model:

This model selectively computes wavelet packet coefficients, and consequently determines the maximum contributing sub-band and calculates the appropriate sampling rate. An incoming signal of 8 KHz is considered and sampled at *i* separate intervals that vary in length and sampling rate by recursively applying a pair of Quadrature Mirror Filters *h (n)* and *g (n)*.

$$x_{j+1}^{2b}(t) = \sqrt{2}\ \sum_m h(m-2k)x_j^b\ (t) \tag{3}$$

$$x_{j+1}^{2b+1}(t) = \sqrt{2}\ \sum_m g(m-2k)x_j^b\ (t) \tag{4}$$

The variable *j* denotes the level of decomposition, *b* denotes the sub-band, and *m* is the number of wavelet coefficients. At each level of decomposition, the QMF's act as high and low pass filters. A wavelet estimator for *x (t)* can be constructed from wavelet coefficients at level *j* by removing or dampening coefficients which are below a threshold. The highest frequency sub-band with any contributing component is passed through this process again. This is repeated until j levels of decomposition have been performed. This threshold is defined as $\lambda = \sigma\sqrt{2logN}$, where N represents the size of the data set and σ is an estimate of signal noise. The wavelet packet transform is an accurate representation of the signal in time-frequency domain; its contents are used as a basis for guiding the sampling rate. Each interval consists of a short investigative sub-interval of length T_H in which a high sampling rate *HSR* is used. The choice of *HSR* is based on a priori knowledge of the signal's highest expected frequency content. A wavelet analysis is then performed on the data points acquired to estimate the frequency spectrum and highest dominant frequency component *MF*. The time required for analysis is included in the interval T_H, where the system continues to sample at *HSR* during the analysis. With the identification of the highest frequency component, an appropriate sampling rate *RSR* is requested as:

$$RSR = c * MF \tag{5}$$

In Equation 5, *RSR* is the required sampling rate, c is a confidence factor greater than 2 to satisfy the Nyquist's theorem, and *MF* is the highest dominant frequency component found in the signal. The remainder of interval i consists of the sub-interval of length T_L in which an adapted sampling rate is used. For increased robustness, the adjusted sampling rate *ASR* is dependent on the requested sampling rate *RSR* in current interval as well in the k previous intervals:

$$ASR = max_i\left(RSR_{(i\ldots l)}\right), l = 0 \ldots . k - 1 \tag{6}$$

C. To calculate the sub interval:

The time interval T_L gives a measure of the duration for which ASR is required. For stable and low activity the *MF* and sampling rate vary slightly hence T_L can be further used to save energy. If the frequency changes suddenly then the interval has to be readjusted to the new event. The modified version of Additive Increase Additive Decrease algorithm is used to achieve this. Here according to the algorithm the adaptive sleep interval is as follows if the current sampling rate is below a threshold then the sampling rate is incremented by α else additively decremented by α. The algorithm also reduces the packet collision in wireless communication.

Since the wavelet packet transform essentially decomposes the signal into separate frequency sub-bands (b), a sampling rate selection rule is defined by modifying equation 5 as equation 7

$$RSR = c\frac{HSR}{2^j}\ (b_{max} + 1) \tag{7}$$

The signal can be reconstructed from the wavelet packet coefficients at level j subjected to a hard threshold λ, an estimator of $x\ (t)$ can be constructed as in equation 8

$$\mathrm{x(t)} = \sum_{b=0}^{2^{j}-1} x_j^b\ (t) I\left(\left|x_j^b(t)\right|\right) \geq \lambda \tag{8}$$

An appropriate sampling rate is selected based on the highest contributing sub-band found currently in the signal, b_{max} as seen in Equation 7. Since the rate switching rule is based solely on the maximum contributing sub-band from the j level wavelet packet transform and a global threshold is used, it is not necessary to perform the entire wavelet packet decomposition. The algorithm can be used to virtually traverse a wavelet packet tree, further decomposing only the highest contributing sub-band at each level. The result is the determination of the highest contributing sub-band b_{max} at level j. The computational complexity in wavelet decomposition is as shown in equation 9 below:

$$O(N) = \sum\nolimits_{j=0}^{j-1} \frac{cN}{2^j} \tag{9}$$

Where, N is the size of the data set and C is the number of coefficients in each wavelet filter.

V. Results and Discussion:

The aim of Adaptive Sampling is to produce an accurate spatial picture of a certain physical process, while making an efficient use of resources like energy and network bandwidth. Since events are not uniformly distributed in the environment, not all sensor nodes should collect data samples at a common fixed rate. Hence Adaptive Sampling Algorithm identifies the minimal sampling frequency guaranteeing reconstruction of the sampled signal and reduces the power consumption of the network by adapting the sample rate to the real needs of the physical phenomena under observation. Here source signals consist of three different components first consists of the spindle and tooth pass frequencies along with their first harmonic, second includes the dominant components emerging with chatter, which rise exponentially until maximum vibration is reached, the third is made up of harmonics from the chatter vibration.

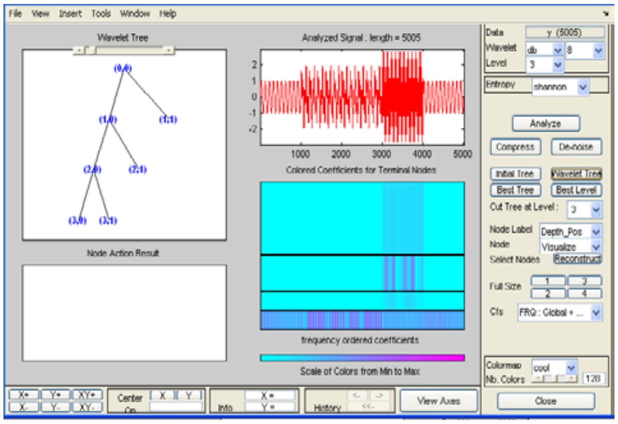

Fig 1: DWT of non-stationary signal *y (t)*

The Discrete Wavelet Transform of non-stationary signal *y(t)* is in Figure. The Signal consists of four different frequency components of 200Hz, 500Hz, 3000Hz and 5000Hz. First 1000 samples have only 200 Hz frequency, from 1000 to 3000 it has 200 Hz and 500 Hz frequency components, from 3000 to 4000 it has 3000 Hz and 5000 Hz frequency components and from 4000 to 5000 again it has 200 Hz and 500 Hz frequency components. This non stationary signal is decomposed first into low pass and high frequency band signal using low pass and high pass filter respectively. Further low pass signal is again decomposed into low pass signal and high frequency band signal. This is continued for j=3 level of decomposition. Tree wavelet structure gives a clear picture of decomposition.

The wavelet decomposition may be calculated using a recursion of these filter-decimation operations. Figure 2 shows a WPD tree for a signal of length eight. The full WPD is displayed as a tree with a discrete sequence at every branch. Each branch sequence is referred to as a bin vector. The decomposition may be continued down to the final level where there is only one element in each bin vector. Note that each bin vector is the result of a linear operation on the original sequence. Unlike DWT in WPD both low frequency band and low frequency band signals are further decomposed and the process is continued for j=3 level of decomposition and this difference is clearly visible in WPD tree.

The proposed algorithm is evaluated on three test signal suitable for grating application with a randomly generated chatter event and adding white Gaussian noise to obtain three different SNR of 40db, 30db and 20db. Daubechies 4 wavelet filters are used in the sampling rate selection algorithm for their short filter length. For the first T_H interval 258 samples are taken at a rate of 8000 samples per second then sampling rate is adjusted in accordance with the signal frequency.

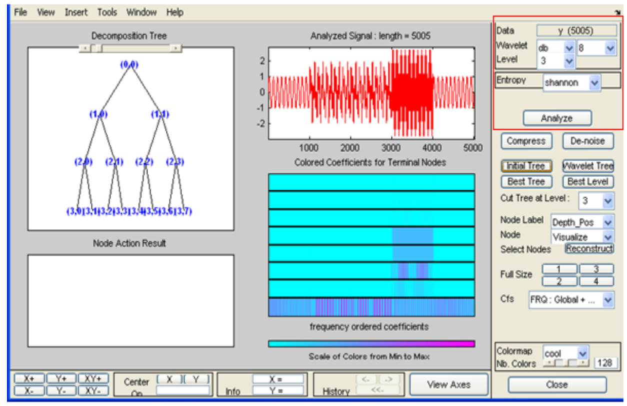

Fig 2: Wavelet Packet Decomposition

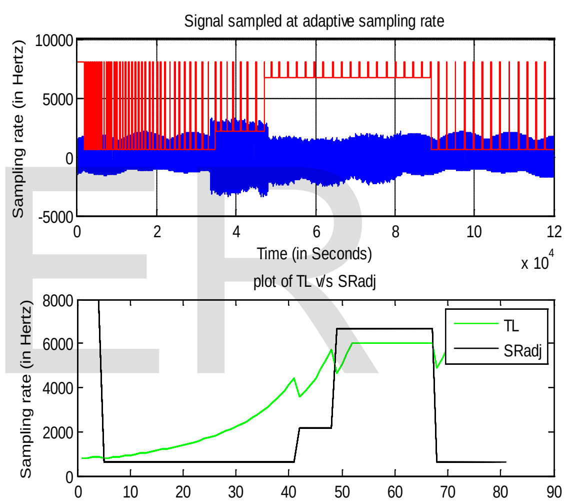

Fig 3: Plot of Signal *y (t)* sampled at ASR.

Energy consumption during adaptive sampling is continuously calculated and summed to give total energy consumption. The hardware constants considered for the processor from the Intel Xscale PXA271 [17] and transceiver from a Maxim converter defined for multiple sampling rates [18].

When the signal is sampled at uniform sampling rate then Energy consumed will be constant and is equal to 3.36 Joules. Unlike uniform sampling, Energy consumed by adaptive sampling rate will be lesser and varies with Signals to Noise Ratio (SNR). Energy consumed by adaptive sampling is computed using equation (10):

$$E_{AS} = E_{com} + E_{adc} + E_{comp} \qquad (10)$$

Where, E_{comp}, E_{com} and E_{adc} are energy consumption in task computation, communication energy and energy consumed by ADC respectively.

Table 2 shows the energy computed for adaptive sampling rate for three test signals with SNR 20db, 30db and 40db. From the table it is clear that energy consumed by adaptive sampling rate is lesser than that of uniform sampling rate of 8 KHz. In other words some amount of energy is saved as compared to uniform sampling rate. The percentage of energy saving is calculated using equation 11:

$$Percentage\ Energy\ Save = \left(1 - \frac{E_{AS}}{E_{fixed}}\right) * 100 \quad (11)$$

Table 2: Energy computed for three Test Cases

Test Case	SNR	E_{adc}	E_{comp}	E_{comm}	% Energy Save
Signal 1	20	0.10057	0.077308	1.0836	65.7893
	30	0.10166	0.080725	1.2363	60.9616
	40	0.098131	0.082775	1.3214	57.7963
Signal 2	20	0.094935	0.076073	0.87715	72.1796
	30	0.4003	0.079679	1.11	64.7004
	40	0.10081	0.076233	1.2537	60.5558
Signal 3	20	0.09929	0.09841	1.3066	57.4583
	30	0.19972	0.072193	1.7139	47.2117
	40	0.2	0.080187	1.703	47.0828

The sampled signal is reconstructed piecewise using a Sinc reconstruction filter. This is done to up sample the signal to one uniform rate for comparison with fixed rate sampling. The signals are compared and the Mean Square Error (MSE) is calculated by using equation 12:

$$Mean\ Square\ Error = E[(\widehat{y(t)} - y(t)] \quad (12)$$

Figures 4 show the original and reconstructed signal along with the spectrograms for the first signal with SNR 20db. From the spectrogram of the original signal it can be seen that lower frequency components exist for all the time, the lower chatter frequencies is present for duration from 1.8 sec to 3 sec, and next higher chatter frequency is present for duration from 2.5 sec to 4.7 sec. If we observe the spectrogram of reconstructed signal all the chatter events are recovered. For the first signal, energy saving is 65.22% and MSE is 0.014486.

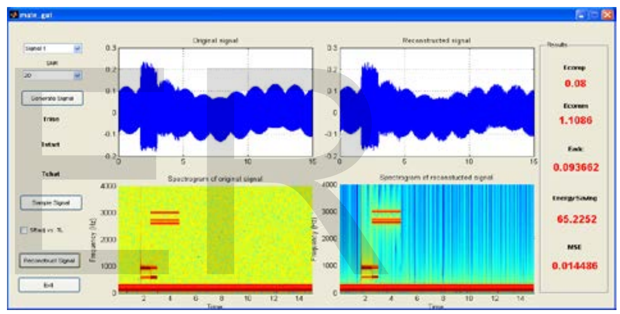

Fig 4: Comparison of Original and Reconstructed Signal *y(1)*

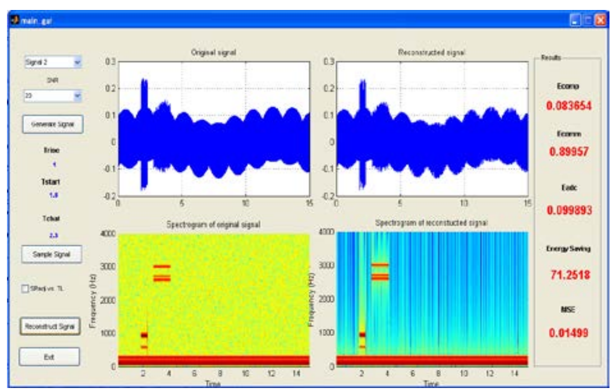

Fig 5: Comparison of Original and Reconstructed Signal y(2)

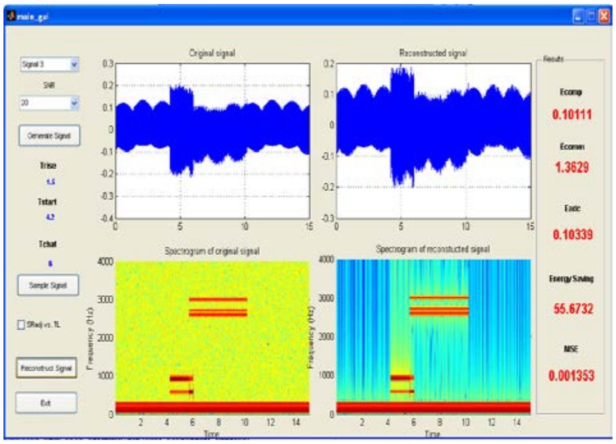

Fig 6: Comparison of Original and Reconstructed Signal y(3)

Figures 5 and 6 shows the original and reconstructed signal along with the spectrograms for the second and third signal with SNR 20db. From the spectrogram of the original signal it can be seen that the lower chatter frequencies is present for duration from 1.8 sec to 2.3 sec, 4.2 sec to 6 sec respectively, and next higher chatter frequency is present for duration from 2.8 sec to 4.1 sec and 5.7 sec to 10.2 sec. If we observe the spectrogram of reconstructed signal all the chatter events are recovered. For the second signal, energy saving is 71.25 % and MSE is 0.01499 and 55.6732 % and MSE is 0.001353 for the third signal.

The simulation results for Mean Square Error (MSE) between the adaptively and fixed rate (8 kHz) sampling of three signals are shown in Figure 7. It is apparent that as the signal to noise ratio decreases, both energy savings and error increase.

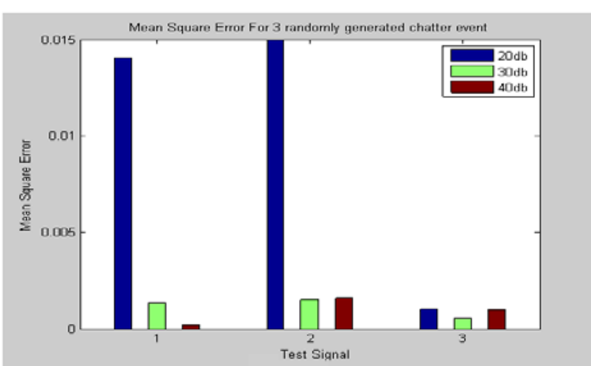

Fig 7: MSE for three different test signals

A decrease in energy consumption indicates that lower sampling rates were more frequently selected, apparent in the sampling rate plots. As the noise level increases it immerses the low amplitude, high frequency signal components and increases the threshold. In this case, detection becomes less likely. The algorithm was found to be capable of performing at even lower SNRs, but required finer tuning specific to the signal type. Examining spectrograms and spectral density of the adaptively sampled signals reveals that the desired signal is retained. The sampling rate remains at a low rate when only lower frequency components are present, then increases to successfully capture the chatter event. As the SNR increases, lowering the sampling rate will filter or alias high frequency noise. This causes a discrepancy between the original and adaptively acquired signal in the time domain, but the desired information is preserved. The adaptive sampling process should be coupled with an adaptive filter to avoid aliasing and effectively remove noise when sampling rate is reduced. Incorporating the additional aliasing filter would result in a system that preserves important signal information and facilitates enhanced energy usage, while simultaneously filtering the signal of high frequency noise.

VI. Conclusions:

The proposed scheme is capable of dynamically adjusting the sampling rate of the acquired signals. The procedure is eventually considered to decrease the energy consumption of a wireless device angle pulsation sensor for grinding application However, the approach is general and it is applicable to other high data rate application where on-line monitoring of signals exhibiting non-stationary behavior is of interest. Mathematical modeling has shown that the method excels in dynamically adjusting sampling rate based on the frequency content of the signal.

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