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An Energy Effective Frequency based Adaptive Sampling Algorithm for Clustered Wireless Sensor Networks

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Abstract. The objective of environmental observation with wireless sensor networks is to extract the synoptic structures (spatio-temporal sequence) of the phenomena of region of interest (ROI) in order to make effective predictive and analytical characterizations. Energy limitation is one of the main obstacles to the universal application of wireless sensor networks. Certainly, there are many researches concerned to energy efficient scheme in wireless sensor networks. Adaptive sampling strategy is regarded as a much promising method for improving energy efficiency in recent years. In this paper, we dedicate to investigating how to regulate sampling frequency of sensor nodes in different clusters dynamically following the change of signal frequency. The algorithm proposed in this literature is called as Adaptive Frequency based Sampling (FAS) algorithm. The key idea of this paper is to measure periodic signal frequency online in different clustered region, afterwards adjust signal sampling frequency following with minimal necessary frequency criterion, as a result, the previous desired level of accuracy is achieved and the energy consumption is decreased. The real data for simulation is derived from Intel Berkeley Research lab and the simulation results are compared with that of fixed sampling rate approach with respect to energy conservation.

Keywords: Wireless Sensor Networks; Adaptive Sampling; Frequency based Sampling; Energy Effective

1. Introduction

Wireless sensor networks [1] have received considerable academia research attention in present years. Wireless sensor networks consist of a large number of tiny sensor nodes deployed over a geographical area, each node is a low-power device that integrates computing, communication and sensing abilities. The key application of wireless sensor networks is monitoring physical phenomena and acquiring environment information. With the advancements in hardware miniaturization and integration, it is possible to produce tiny cheap sensor devices that combine sensing with computation, storage, and communication. Availability of such devices has made it possible to deploy them in a networked setting for applications, such as wildlife habitat monitoring [2], wild-fire prevention [3], and environmental monitoring [4], and so on.

Typically, each sensor node collects raw sensory data which is needed to be delivered to the users through network interconnection for further analysis. The simplest way is to permit each sensor node to deliver its raw sensory data to the base station periodically, where the data can be assembled for subsequent analysis. However, this approach results in excessive communication and the energy is wasteful. Energy limitation is one of the main obstacles to the universal application of wireless sensor networks. In recent years, several energy management schemes have been proposed for reducing the power consumption in the literatures, the novel one is adaptive sampling. It is emphasized that reducing the amount of acquired data by using adaptive sampling techniques aloes reduces the energy consumption for communication. A detailed survey can be found in [5], which assumes that data acquisition and processing have an energy consumption which is significantly lower than that of communication.

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Generally, data acquisition and processing consume energy that is significantly lower than that of communication. Therefore, traditional researches are concerned with how to conserving energy as much as possible by reducing transmission capability. Unfortunately, this assumption does not always hold in a number of practical applications because acquisition times are typically longer than transmission or some sophisticated acquisition process such as multimedia sensor networks.

We propose a Frequency based Adaptive Sampling (FAS) algorithm here to solve the problem of how to regulate sampling frequency of sensor nodes dynamically following the change of signal frequency. The key idea of this paper is to measure periodic signal frequency online, afterwards adjust signal sampling frequency to the real needs of the physical phenomena under observation. As a result, these two complementary requirements can be achieved: the previous desired level of accuracy is achieved through guaranteeing certain minimal sampling rate for reconstruction, e.g., Nyquist sampling frequency; moreover, the energy consumption is decreased through reducing sampling frequency rate of sensor nodes as much as possible. FAS algorithm does not assume any hypothesis with regard to the observed signal, therefore, it is of more general applicability. For large-scale wireless sensor networks with many clusters, signal evolution rates of different clustering regions are different, therefore, signal sampling rate ought to adjust subsequently following signal evolution tendency of different clusters.

In this paper, we propose an energy effective adaptive sampling algorithm considering temporal correlation in clustered wireless sensor networks, which is named as FAS algorithm. The paper is organized as follows. Section 2 introduces some related works. Section 3 presents FAS algorithm in details. Simulation environment and results are finally presented in Section 4. Section 5 is the conclusion of this paper.

2. Related Works

The problem of energy efficient transmission has been investigated with certain technology such as mathematical optimization in the current literatures [7-8]. However, most researches are concerned with energy efficient transmission, not energy efficient sampling. Unfortunately, data acquisition or sampling will consume much more energy than data transmission in a number of practical applications because acquisition times are typically longer than transmission or some sophisticated acquisition process such as multimedia sensor networks. Therefore, some researchers have been investigating energy efficient sampling scheme.

Temporal correlation was used in an adaptive sampling algorithm for minimizing the energy consumption of a snow sensor [9]. A similar approach has been suggested in [10], where the sampling rate is adapted based on the outcome of a Kalman filter. Adaptive sampling is also proposed in [11], in which a flood alerting system is presented. The system includes a flood predictor that is used to adjust the reporting rate of individual node. Other researches illustrated in [12-15] are discussing how to perform energy efficient sensory data sampling.

All the above energy efficient sampling algorithms are dedicated to conserving energy of sensor nodes. As a result, these schemes are named as adaptive sampling algorithms. Fig.1 illustrates categories of current adaptive sampling algorithms, which are concluded in a lot of literatures by us.

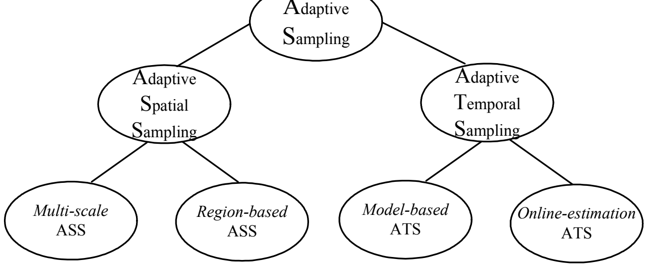

Fig. 1: Sampling algorithm category

Generally, adaptive sampling schemes can be divided in two categories: one is adaptive spatial sampling scheme and the other is adaptive temporal sampling scheme. Adaptive spatial sampling schemes assure monitor accuracy using region location adjustment or wake-up state scheduling. Adaptive temporal sampling schemes assure monitoring accuracy using sampling frequency adjustment or online model estimation of signal tendency. Certainly, there are a few mutational adaptive sampling schemes such as multi-scale adaptive sampling, which provides multi-resolution sensory information as possible as required.

There are only a few researches concerned to temporal sampling schemes for wireless sensor networks. Lygouras [16] presented a nelocity-adaptive measurement system for closed-loop position control that relies on the adaptation of the sampling frequency to improve the response time. Aplippi [17] proposed an adaptive sampling algorithm (ASA) that adapted the sampling frequencies of the sensors to the evolving dynamics of the process. ASA reduced the power consumption of the measurement phase by adapting the real needs of the physical phenomena under observation, however, it is a centralized approach but not adaptable for large-scale wireless sensor networks. In this paper, we dedicate to studying adaptive temporal sampling by regulating sampling rate adaptively and proposing a novel adaptive frequency based sampling algorithm. To the best of our knowledge, this is the first novel approach for clustered adaptive frequency based technology. By adaptively sampling the region of interest (ROI) of different clusters, the sampling rate decreases energy consumption, moreover, the necessary sensory accuracy is guaranteed.

3. FAS Alogorithm

As we known, following the most famous Nyquist law in signal processing field, if the highest frequency $F_{\max}$ of signal is given, the minimum sampling frequency F_N is more than at least twice the highest frequency so that signal reconstruction is guaranteed [18]. In particular, it is common to pick a sampling frequency three to five times higher than the signal maximum frequency [19], i.e., $F_N = cF_{\max}$, where c=3-5 generally.

First of all, the principle of adaptive frequency sampling algorithm proposed in this paper is explained with Fig.2. In Fig.2, a specific signal with amplitude shifting with time is figured. Fixed sampling rate by Nyquist law is illustrated in Fig.2 (A), and over-sampling and under-sampling cases are illustrated in Fig.2 (B) and Fig.2 (C). Obviously, over-sampling denotes that the sampling rate is much higher than necessary Nyquist sampling rate, and under-sampling denotes that the sampling rate is low than necessary Nyquist sampling rate. Consequently, design appropriate and necessary sampling rate to satisfy certain accuracy and minimal energy consumption is a promising but difficult mission.

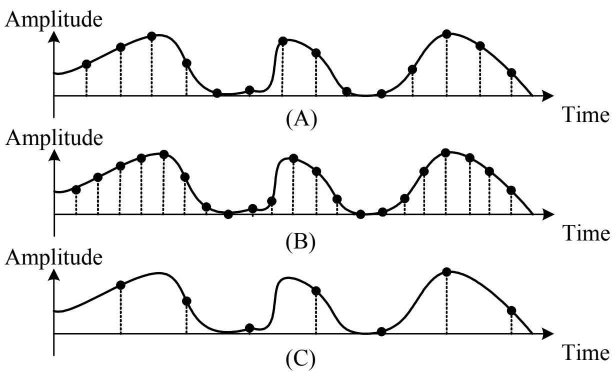

Fig. 2: Over-sampling and Under-sampling

Unfortunately, signal maximum frequency is not available priory and changes over time in a non-stationary process. Consequently, the sampling frequency has to change adaptively following change tendency. For large-scale wireless sensor networks with many clusters, signal evolution rates of different clustering regions are different, therefore, signal sampling rate ought to adjust subsequently following signal evolution tendency of different clusters. Therefore, our proposed FAS algorithm must be operated on different clustering regions.

There are three procedures that form FAS approach: clusters construction phase, sampling frequency regulation within clusters phase, data delivery between clusters phase. Now we will illustrate the details in the followings.

3.1. Clusters Construction

In the first phase, sensor nodes establish different clusters autonomously and elect cluster head (CH) in a fully distributed fashion. Our design proposes a simple distributed clustering algorithm named maximum energy & minimum distance (MEMD) clustering algorithm to establish one-hop clusters, which is described in below. First of all, the weight value of sensor node to elect CHs is defined as:

$$\omega(i) > \omega(j) \Leftrightarrow E(i) > E(j) \text{or } E(i) = E(j) \ \&\& \ id(i) > id(j) \tag{1}$$

where $E(i)$ and $E(j)$ denote the residual energy of sensor node i and j respectively, $id(i)$ and $id(j)$ denote ID number of sensor node i and j respectively. It is obvious that the defined weight is positive correlation with node residual energy, and the ID value of sensor node is the second factor. More specially, sensor nodes with more residual energy within all the neighbor nodes should be chosen to be cluster heads with higher probability, thus implementing maximum energy first principle. After cluster heads election, each cluster member sensor node will select the nearest CH and join that cluster. It is required that the distance between each cluster member and its nearest CH must smaller than maximal transmission power radius $R_{\max}$. The MEMD clustering algorithm is described in Fig.3, and an example of MEMD clustering algorithm is shown in Fig.4.

 # Node i clustering procedure;
begin
$Broadcast(ID, position, E_R);$
Receive beacon from all neighbour nodes $j \in N_i$;
Compare the weight value with ID and E_R;
$if\,(\omega_i \geq \omega_j \quad \forall j \in N_i)\{$
  Node i becomes Cluster Head(CH);}
else{
  $\omega_k > \omega_j \quad \forall k, j \in N_i$
  Vote Node k to become Cluster Head(CH);
}
for(each non-CH node i){
Node i join in nearest Cluster Head;}
end

Fig. 3: Pseudo-code of Max Energy & Min Distance clustering algorithm

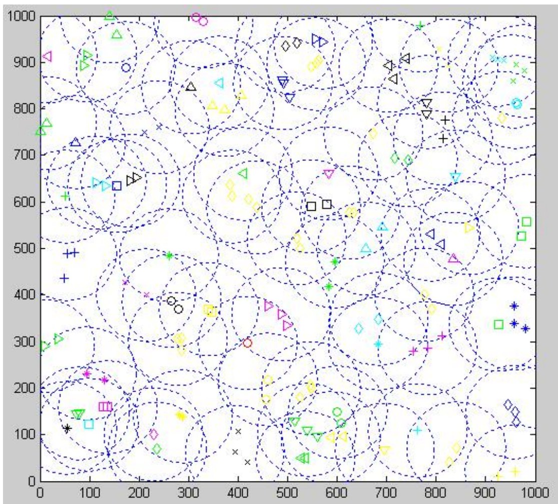

Fig. 4: Clustering Results (400 sensor nodes randomly distributed in a region of 1000×1000 and Rmax=100)

Generally, any region-based environment aware clustering algorithms are appropriate for FAS approach, the previous MEMD clustering algorithm is a typical one of them. The detailed constitutions of interactive messages for clustering are omitted for simpleness.

3.2. Intra-cluster Sampling Frequency Regulation

Within each cluster, sensor nodes are divided into two categories: one particular sensor node is elected as CH which is responsible for data aggregation, and the other sensor nodes as cluster members (CMs) that are responsible for data acquisition. The most important assumption of this paper is the region of interest (ROI) within each cluster is data correlated and variation identical. Therefore, the sampling frequencies of sensor nodes in the same cluster ought to be same. The distibuted nature of FAS algorithm is that different sampling frequency regulation processes are operated in different clusters at the same time, therefore, FAS algorithm is appropriate even for large-scale sensor networks.

The primary and diffucult problem is to estimate the maximal frequency of phenomena signal within certain cluster. Unfortunatly, precise estimation of signal maximal frequency is hard, so we use a heuristic method for sampling frequency modification in this paper. In each iteration, CH broadcasts a certain sampling frequency to all CMs which is derived by current sensory accuracy. If the acquired sensory acuracy is low than the threshold value θ, then increases sampling rate $f_c = f_c + \beta$ $(\beta = \frac{Th_{\max} - Th_{\min}}{M})$. On the contrary, if the acqurired sensory accuracy is large the threshold value θ, then decreases the sampling rate $f_c = \alpha \times f_c$ $(\alpha = 0.5 - 0.8)$. The sampling frequency regulation scheme obeys multiplicative increase additive decrease (MIAD) rule. The details are illustrated in the Fig.5. The parameters used in this algorithm comprise of α, β, $Th_{\max}$, $Th_{\min}$, M and T.

#Cluster i Sampling Frequency Regulation procedure
begin
Given initial sampling frequency f_i;
CH broadcast f_i;
while(*each Time interval* T)
{
CH receive data and aggregation;
CH calculate sensory accuracy;
if (*sensory accuracy* $\geq \theta$)
  $f_c = \alpha \times f_c \qquad (\alpha = 0.5 - 0.8)$
else
  $f_c = f_c + \beta \qquad (\beta = \frac{Th_{\max} - Th_{\min}}{M})$
if $(f_c \geq Th_{\max})$ $f_c = Th_{\max}$; *if* $(f_c \leq Th_{\min})$ $f_c = Th_{\min}$
CH broadcast f_c;
}
end

Fig. 5: Pseudo-code of intra-cluster sampling frequency regulation

The remaining problem is how to calculate sensory accuracy online by CH. In our method, sensory accuracy is defined as message delivery ratio for simpleness (i.e., the percentage of messages correctly received by the CH node). In order to improve transfer reliability in wireless sensor networks, serveral retransmission manners such as ACK are used. Therefore, the impact of communication unreliability will influence the performance of FAS algorithm, nevertheless, the influence of the communicaiton relibaility has not been studied in this paper.

3.3. Inter-clusters Data Delivery

The final phase is inter-clusters data delivery from CHs to the base station. Although sampling frequencys of different clusters are different, CHs transmit aggregated data to the base station with the same frequency *T*. Actually, the delivery ratios of different CHs can be different with different regions, because the signal evolution over time in each region is different. The relay method between sensor nodes is the same with tranditional routing schemes.

4. Performance EvAluation

In this section, we describe the evaluation settings and the metrics we have chosen for the evaluation. In order to verify the performance of FAS algorithm, some simulations are carried out with a series of fancied data. The evaluation metrics comprise of sampling frequency f_c and energy consumption rate comparing with fixed sampling rate. In our simlulations, some important parameters of FAS algorithm are defined in Tab.1.

Table.1 FAS Parameters for Simulations

Parameter	Value
Th_{max}	80 Hz
Th_{min}	20 Hz
M	10
α	0.5-0.8
T	10 Samples

The half value of actual sampling frequency fc/2 and the signal frequency are described in Fig.6. The original sampling frequency is defined as $(Th_{max} + Th_{min})/2$=50Hz. It is obvious that the change of sampling frequency drops behind that of signal maximal frequency with windows M=10 samples from Fig.6. Moreover, the actual sampling frequency approaches the maximal frequency of signal. Therefore, the sampling frequency derived from FAS algorithm is better than fixed sampling frequency.

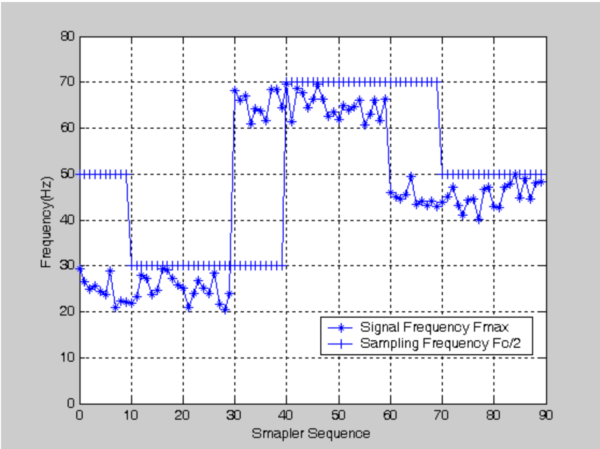

Fig. 6: Sampling frequency following signal frequency evaluation

The energy consumption ratio is defined as the rate of actual sampling frequency with maximal frequency threshold which is set as 100Hz in our simulations. The results are illustrated in Fig.7. As we know, if the actual signal frequency increases, the sampling rate ought to increase, thus consuming much more energy, therefore, energy consumption ratio will increase because of the fixed maxmial frequency threshold Th_{max} .

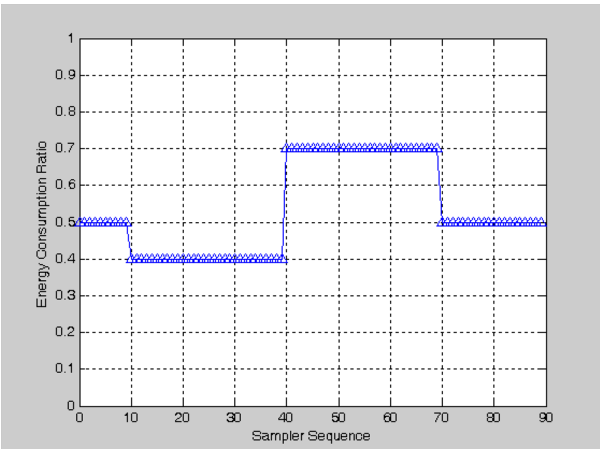

Fig. 7: Energy Consumption Ratio

5. Conclusions

In this paper, we proposed an energy efficient adaptive sampling algorithm based on adaptive sampling frequency which regulates sampling frequency of related sensor nodes so as to reduce energy consumption intelligently. However, most of the proposed solutions are limited to either temporal or spatial correlation. Our future works are dedicated to finding more energy-efficient approach using the spatio-temporal correlation of wireless sensor networks. Moreover, in our next simulations, we will use real sensory data which is derived from Intel Berkeley Research lab [20]. There are 54 sensor nodes deployed in the lab between February 28th and April 5th, 2004. Four parameters including temperature, humidity, light and voltage are monitored.

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