An Enhanced Energy Saving Approach for WSNs

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Abstract

Wireless sensor networks are used today in a wide range of applications, all of which employ a large number of sensors. In large scale sensor networks, sensor nodes are often not easily accessible. Because of this, the energy consumption of wireless networks is an important matter as well as a popular topic of research. A sensor node consumes energy while collecting, processing, transmitting and receiving data. Each of these processes could be the focus of research, so there are many investigations into these subjects, centering on ways of reducing energy consumption and extending the lifetimes of networks.

In this paper we study data processing schemes that define the distribution of decision making, which affects system accuracy and energy consumption. The two typical detection schemes are the centralized and distributed schemes. In a centralized scheme, nodes collect samples from the environment and send them to a "fusion center", where the samples are used to arrive at a final decision. This scheme provides optimal decision accuracy; however, it consumes considerable energy. In contrast, distributed schemes allow nodes to make local 1-bit decisions, which are sent to the fusion center to make the final decision. In a hybrid scheme the network specifies the level of accuracy required for the whole system. This can be achieved by manipulating the scheme to work sometimes as centralized other times as distributed. We propose an energy-saving hybrid scheme that focuses on optimizing transmission energy, since most of the energy consumed is in the transmission process. In the proposed scheme each node alternates between centralized and distributed according to its location and path length. Nodes with longer path lengths are classified as acting more as distributed than those with shorter path lengths.

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1. Introduction

The function of sensors is to convey physical phenomena to the digital world by capturing and

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revealing real-world behaviors and converting these phenomena into a form that can be processed, stored, and acted upon. With sensor capabilities a tremendous societal benefit is achieved when sensors are integrated into available devices, machines, and environments. They can help to avoid infrastructure failure disasters, protect precious natural resources, enhance security and enable new "smart" applications such as context-aware systems and home technologies. Wireless sensor networks are based on numerous advanced technologies such as very large scale integration (VLSI), micro-electromechanical systems (MEMS) and wireless communications. The development of these technologies is contributing to a wider application of WSNs. For example, with the enhancement of MEMS technology, sensors are becoming smaller, and developments in semiconductor technologies are producing smaller microprocessors with higher processing capacities. The improvement of computing and sensing technologies is enabling the development of flexible WSNs, which can be widely applied [1] [2].

Monitoring environmental changes and detecting specified events is the main function of sensor networks. This function is achieved through four basic components of a sensor network [3]: distributed or localized sensors, an interconnecting network – most often wireless based, a central point of information clustering a set of computing resources at the central point or network core to handle data collecting, event trending, status querying, and data mining. WSNs use centralized fusion centers (sinks), which work as cluster gateways, and many distributed sensors (motes) [4]. These sensors sense and send observations to the centralized unit. The centralized unit decides if an event is initiated or not.

Most of the power consumed in a network is used in processing, transmitting and sensing. Until now limited power resources for sensors has been the main constraint in WSNs. It is very important to reduce sensor power consumption while maintaining acceptable detection accuracy according to application requirements. Many researchers have focused on the above three processes [5], attempting to enhance the power consumption efficiency of the sensors for each of them. Some schemes enhance the operating system and reduce the required processing cycles; other schemes optimize the RF part including collision space and noise filtering. This thesis focuses on schemes which study decision processing and transmitting where those schemes define how to collect observations (sampling rate), where to process them (locally or centralized) and the data to be sent from nodes to the fusion center, which will affect the degree of loss of data and accuracy [6]. The main goal of this paper is to produce an optimum controlling scheme that extends network/sensor lifetime by reducing power consumption and maximizing the network efficiency and accuracy. Our proposed scheme balances between the reduction of data transmission and processing by distributing these two activities among the nodes and the central unit (sink).

2. Related Work

There are two traditional detection schemes: the centralized detection scheme and the distributed detection scheme, the methodologies of which will be covered in details. In our approach, we use a tree topology where nodes are "independently and identically distributed" (i.i.d.). They are connected to the FC through a multi-hop route, where nodes also act as hops to receive data from child nodes and forward it to the Fusion Center (FC) with any processing, encryption or encoding. The focus here is only on accuracy and energy consumption, and it is assumed that lower layers are working perfectly and that there is no efficiency problems caused by RF or by packet collisions, i.e. there is no data retransmission.
2.1. Bayesian Decision Theory

2.1.1. Binomial Distribution

A Bernoulli trial can result in a success with probability \( p \) and a failure with probability \( q = 1 - p \). Equation (1) gives the probability distribution of the binomial random variable \( x \). The number of successes in \( n \) independent trials is:

\[
f(x; n, p) = \Pr(x|p) = \binom{n}{x} p^x (1 - p)^{n-x}
\]

The probability that two events, \( A \) and \( B \), will both occur will be \( P(A \cap B) = P(B \cap A) = P(B)P(A|B) = P(A)P(B|A) \). From this formula the main Equations (2) and (3) of Bayes’ Rule can be derived:

\[
P(A|B) = \frac{P(A)P(B|A)}{P(B)} \tag{2}
\]

\[
P(A) = \sum_{i=1}^{k} P(B_i \cap A) = \sum_{i=1}^{k} P(B_i)P(A|B_i) \tag{3}
\]

The distribution of \( H \), given \( D \), which is called the posterior distribution, where \( P(D) \) is the marginal distribution of \( D \), is given by Equation (4),

\[
P(H|D) = \frac{P(D|H)P(H)}{P(D)} \tag{4}
\]

Bayes Decision: Choose event happened if \( P(H_1|D) \geq P(H_0|D) \) otherwise choose not happened.

2.2. Centralized Detection Schemes

In centralized detection schemes a network will have \( K \) number of nodes. These nodes will collect \( T \) samples of observations from the environment every specific period, and they will send \( T \) samples together at the end of the period. At the fusion center \( D = [T \times K] \) samples will be received.

According to Bayes, a final decision can be calculated as shown in Equation (5):

\[
\hat{H} = \begin{cases} 
1, & P(H_1|D) \geq P(H_0|D) \\
0, & \text{otherwise}
\end{cases}
\]

The probability of error can be calculated using the following equation:

\[
P_e = (p \times P_{false positive}) + ((1 - p) \times P_{false negative}) \Rightarrow
\]

\[
P_e = p \times P[H' = H_1|H_0] + (1 - p) \times P[H' = H_0|H_1] \Rightarrow
\]

\[
P_e = p \times [1 - P(n \geq \gamma_{FC}|H_2)] + (1 - p) \times P(n \geq \gamma_{FC}|H_0) \tag{6}
\]

To calculate power consumption for the whole network in Equation (7), the following equation can be used, where \( E = \text{total energy}, E_T = \text{transmission energy}, E_R = \text{receiving energy} \) and \( E_p = \text{processing energy} \):

\[
E = E_T + E_R + E_p \Rightarrow E = \sum_{i=1}^{K} (L_i \times T \times e_t) + \sum_{i=1}^{K} (L_i \times T \times e_r) \Rightarrow
\]

\[
E = \sum_{i=1}^{K} (L_i \times T \times (e_t + e_r)) \tag{7}
\]

2.3. Distributed Detection Scheme

In this scheme nodes collect data and make local decisions according to these observations and conclude the event appearance as a 1-bit result. This result is sent to the fusion center to make a final decision according to the collected 1-bit results from all nodes. In this scheme data accuracy between nodes and the fusion center has been lost.
We propose \( K \) number of nodes; these nodes will collect \( T \) samples of environmental observations with \([n_i = \text{number of 1's for node } i]\) and will send a 1-bit local decision every specific period.

At the fusion center, \( D = [1 * K] \) samples will be received.

According to Bayes, a local decision can be calculated as shown in Equation (8):
\[
\hat{H}_i = \begin{cases} 1, & P(H_1|n_i) \geq P(H_0|n_i) \\ 0, & \text{otherwise} \end{cases}
\]

From equation (1) and (5), we can calculate local decision as shown in equation (9):
\[
P(H_1|n_i) \geq P(H_0|n_i) \quad \Rightarrow \quad \frac{P(n_i|H_1) P(H_1)}{P(n_i)} \geq \frac{P(n_i|H_0) P(H_0)}{P(n_i)} \quad \Rightarrow \quad \frac{P(n_i|H_1) P(H_1)}{P(n_i|H_0) P(H_0)} \geq \frac{P(H_0)}{P(H_1)}
\]

\[
\hat{H}_i = \begin{cases} 1, & n_i \geq \gamma_{local} \\ 0, & \text{otherwise} \end{cases}
\]

For final decision we collect \( b = \text{total 1's if local decision} \hat{H} \), the probability of error can be calculated using Equation (11) below:
\[
P_e = \left( p * P_{false positive} \right) + \left( (1 - p) * P_{false negative} \right)
\]

\[
P_e = \left( p * \left[ 1 - P(b \geq \gamma_{FC}|H_1) \right] \right) + \left( (1 - p) * P(b \geq \gamma_{FC}|H_0) \right)
\]

To calculate power consumption for the whole network Equation (12) can be used, where \( E = \text{total energy}, E_T = \text{transmission energy}, E_R = \text{receiving energy} \) and \( E_P = \text{processing energy} \):
\[
E = E_T + E_R + E_P \Rightarrow E = \sum_{i=1}^{K}(L_i \ast 1 * e_i) + \sum_{i=1}^{K}(L_i \ast 1 * e_o) + \sum_{i=1}(T \ast e_p)
\]

\[
E = \sum_{i=1}^{K}(L_i \ast (e_i + e_o)) + \sum_{i=1}(T \ast e_p)
\]

2.4. Hybrid Detection Scheme

Neither the centralized nor the distributed detection scheme is flexible enough for designers to choose between detection accuracy and energy consumption. Lige Yu et al [7] proposed a hybrid scheme that balances detection accuracy and total energy consumption. According to a defined level of accuracy, the nodes will vary between sending all collected data and sending a 1-bit result. Thus, such schemes attempt to balance accuracy and energy consumption.

In this scheme, assume there are \( K \) number of nodes. These nodes will collect \( T \) samples of environmental observations with \([n_i = \text{number of 1's for node } i]\). There will be upper and lower bounds \( N_0 \) and \( N_1 \), where \( 0 \leq N_0 < N_1 \leq T \). The node result will be 0 if the number of 1’s is less than \( N_0 \). In other words, if the number of 0’s collected is greater than or equal to \( T-N_0 \), 1 will be sent if the number of 1’s are greater than or equal to \( N_1 \). Otherwise all the collected data will be sent, as shown in Equation (14):
\[
\text{Result}_i = \begin{cases} 1, & n_i \geq N_1 \\ n_i, & N_0 < n_i < N_1 \\ 0, & n_i \leq N_0 \end{cases}
\]

From Equation (12), assume that out of \( K \) sensor nodes, \( t \) nodes send 1’s, \( s \) nodes send 0’s and \( K - s - t \) nodes send all their observations. The total data sent, \( \Omega \), will be:
From Equation (12) we can derive the following probability:

\[ P[b = 0|H_0] = \sum_{i=0}^{N_0} (\binom{t}{i}) p_0^i (1 - p_0)^{t-i} \] \[ P[b = 1|H_0] = \sum_{i=N_1}^{T} (\binom{t}{i}) p_0^i (1 - p_0)^{t-i} \]

\[ PD = (\binom{t}{s}) (P[b = 0|H_0])^s (P[b = 1|H_0])^{t-s} \]

\[ PF = (\binom{t}{s}) (P[b = 0|H_0])^s (P[b = 1|H_0])^{t-s} \]

Following from Equations (13) and (14), the final probability of error can be determined using Equation (15):

\[ P_e = p \times [1 - PD] + (1 - p) \times PD \]

To calculate power consumption for the whole network Equation (13) can be used, where \( E = \) total energy, \( E_T = \) transmission energy, \( E_R = \) receiving energy and \( E_P = \) processing energy:

\[ E = E_T + E_R + E_P \Rightarrow E = [\sum_{i=1}^{s+1}(L_i \times 1 \times e_t) + \sum_{i=1}^{K-s-t}(L_i \times T \times e_t)] + [\sum_{i=1}^{s+1}(L_i \times 1 \times e_r) + \sum_{i=1}^{K-s-t}(L_i \times T \times e_r)] \]

\[ E = \sum_{i=1}^{s+1}(L_i \times (e_t + e_r)) + \sum_{i=1}^{K-s-t}(L_i \times T \times (e_t + e_r)) + \sum_{i=1}^{K}(T \times e_p) \]

3. System Model (TELOS)

In order to evaluate and develop our scheme, the behavior of WSN sensors should be understood, and a power consumption model should be defined [8] For this purpose the typical operation conditions of TelosB have been selected as a basis for our power model[9][10].

4. Enhanced Hybrid Detection Scheme

The hybrid scheme adjusts the behavior of the network to vary between centralized and distributed schemes, and also establishes \( N_0 \) and \( N_1 \) parameters to define that behavior, and \( Y \) is the number of observations equal to 1. We propose to enhance the hybrid scheme by dynamically choosing the \( N_0, N_1 \) parameter instead of its being static.

In the hybrid scheme if \( Y \) is between \( N_0 \) and \( N_1 \) the node will act as centralized; otherwise it will act as distributed, as shown in Fig. . For the special case \( N_1-N_0\leq 1 \) the node will always act as distributed, and the node will act more centralized if \( N_1-N_0 \) becomes larger (until \( N_0=0 \) and \( N_1 = MAX \)).

**Fig. 1. Node Behaviour Depends on N0 and N1**

However, \( N_0 \) and \( N_1 \) can be made dynamic, with a preference for a distributed orientation for nodes with longer route paths; for the remaining nodes it can remain more centralized, as in the original hybrid scheme, according to the requirements of the application.

For every sensor \( S \) is varied from 1 to \( K \) we will assign specific \{\( N_0i, N_1i \}\}. These sensors will be classified according to the route path:

\[ S_i = \begin{cases} 
1, & n_i \geq N_{1i} \\
,n_0, & N_{0i} < n_i < N_{1i} \\
0, & n_i \leq N_{0i}
\end{cases} \]

Since \( 0 \leq N_0 < N_1 \leq T \), we will have a finite number of combinations for \( N_0 \) and \( N_1 \). These combinations - or groups of them - should be mapped to all sensors, depending on sensor path weight.
The above mapping is a normal n-to-one mapping problem, which in our case can be solved experimentally by testing it in different deployed wireless sensor applications.

In our scheme, every node will have certain parameters that are defined during the manufacturing phase or by the developer during network deployment, i.e. sampling rate (T), CPmin and CPmax. All nodes are classified according to path length to Z zones. We have here a random WSN where maximum path = 6, which means 6 different zones. Fig. shows an example of WSN nodes classified into zones:

Fig. 2. Network Zones Classification

For our network we will define Minimum CPmin and Maximum CPmax, where CPmax is the maximum CP combination that can be assigned for Zone 1, and CPmin is the minimum CP that can be assigned to the next zones (where all CP <= CPmin).

Out of K sensor nodes, t nodes send 1’s, s nodes send 0’s and k – s – t nodes send all their observation so total send data Ω will be: Ω = {1,...,1; n₁, ..., nₖ₋ₖ₋₁; 0, ..., 0;}. Our final decision, based on Bayes’ Rule, is H’ – H1 if P[H₁|Ω] ≥ P[H₀|Ω]. From the above rule we can derive the following relations:

\[
\frac{P[H₁|Ω]}{P[H₀|Ω]} \geq \frac{1-p}{p}
\]

where CPmax is the maximum CP combination that can be assigned for Zone 1, and CPmin is the minimum CP that can be assigned to the next zones (where all CP <= CPmin).

By applying “Telos” power model, the power calculation is as following: Processing Power = 15 * 10⁻⁶ mA/sample, Rx power = 92 * 10⁻⁶ mA/bit, Tx Power = 84 * 10⁻⁶ mA/bit and T=5. The performance of the four schemes is depicted in Fig. 3.

5. SIMULATION Results

5.1. Power Consumption:

By applying “Telos” power model, the power calculation is as following: Processing Power = 15 * 10⁻⁶ mA/sample, Rx power = 92 * 10⁻⁶ mA/bit, Tx Power = 84 * 10⁻⁶ mA/bit and T=5. The performance of the four schemes is depicted in Fig. 3.
5.2. Accuracy behavior:

In our simulation we are able to get the same result which is given in [7][11][12], where we used in hybrid (N0,N1) = (1,3), (1,4) and (0,4) as shown in Fig. 4.

The performance of the four schemes is shown in Fig. 5, as we can see that enhanced scheme outperforms other schemes.
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Conclusions

The primary purpose of this paper is to enhance the event collection and detection capability of current WSN schemes. Two of the available schemes – centralized and distributed schemes - are basic and have no flexibility. The third scheme – the hybrid scheme– uses the two previous schemes to balance accuracy and energy; nevertheless all the nodes remain with fixed configuration and limited flexibility. In contrast to earlier schemes, the proposed scheme is designed to be more flexible in order to balance the power consumption and the detection accuracy at the node level. Every node is flexible in deciding how to behave, i.e. whether to be more centralized or distributed.

As can be seen from the simulation results, our scheme saves a substantial amount of energy compared to the hybrid scheme, while it retains accuracy to almost the same degree. In addition, our scheme deals more efficiently with larger network area and denser node-number.

References

[1] Ittipong Khemapech, Alan Miller, and Ishbel Duncan, "Simulating Wireless Sensor Networks," University of St Andrews, St Andrews, 2005.
[2] Waltenegus Dargie and Christian Poellabauer, FUNDAMENTALS OF WIRELESS SENSOR NETWORKS, THEORY AND PRACTICE. UK: A John Wiley and Sons, Ltd., Publication, 2010.
[3] Mawan Ihsan Shukur, Lee Sheng Chyan, and Vooi Voon Ya, "Wireless Sensor Networks:Delay Guarentee and Energy Efficient MAC Protocols," World Academy of Science, Engineering and Technology, vol. 50, no. 2009, pp. 1062-1066, 2009.
[4] Thomas Haenselmann, Sensornetworks., 2006.
[5] Jon S. Wilson, Ed., Sensor Technology Handbook. USA: Newnes, 2005.
[6] Chris Townsend and Steven Arms. (2004) Wireless Sensor Networks: Principles and Applications.
[7] Lige Yu, Lin Yuan, Gang Qu, and Anthony Ephremides, “Energy-Driven Detection Scheme with Guaranteed Accuracy,” (2006) IPSN'06, pp. 284-291.
[8] http://www.memsic.com/products/wireless-sensor-networks/wireless-modules.html.
[9] Joseph Polastre, Robert Szewczyk, and David Culler, "Telos: Enabling Ultra-Low Power Wireless Research," in IPSN 2005. Fourth International Symposium on Information Processing in Sensor Networks, 2005, pp. 364 - 369.
[10] (2003) TelosB Mote TPR2420: Datasheet. Datasheet.
[11] Fan Bai, Kumudu S. Munasinghe, Abbas Jamalipou, “Accuracy, latency, and energy cross-optimization in wireless sensor networks through infection spreading,” International Journal of Communication Systems, Vol. 24, Issue. 5, pp. 628-646, 2011.
[12] Kenyeres, Jozef ; Kenyeres, Martin ; Rupp, Markus ; Farkas, Peter, “WSN Implementation of the Average Consensus Algorithm,” Sustainable Wireless Technologies (European Wireless) 2011, pp. 139-146.