

On the Type-2 Fuzzy Thresholding Protocol For Event-Driven Wireless Sensor Networks

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Abstract—Network lifetime is one of the most vital issues in wireless sensor network and is fundamental to any design and development effort. Extending the life time requires energy efficiency in every aspect. Besides, fuzziness, a feature of imperfect information was used to measure the distances between the sensed values. Involved with type-2 fuzzy sets, an effectively thresholding method is proposed and discussed in this study. Given an adaptive threshold value, the membership function of a sensed value is implemented, and the potential improvement gained by using our method is demonstrated by the simulated results presented.

Keywords—type-2 fuzzy sets, entropy, measures of fuzziness, wireless sensor network

I. INTRODUCTION

Over the last half a century, computers are becoming small and cheap, the single-purpose computers with embedded sensors are practical from both economical and theoretical points; the revolution has been taking place. Wireless sensor networks (WSNs), which combine wireless network and context aware computations as the next logical step, make the technology easy enough to be implemented by non-specialists [1]. Though a range of impending applications are envisaged in the area of WSNs, which are categorized as event driven monitoring, continuous monitoring and hybrid methods.

In event driven monitoring application, sensors derived the data packet when events are triggered. On the other hand, in continuous monitoring approach, data was generated continuously with a predefined reporting frequency. The representativeness is to aggregate data in a cluster-based architecture with low energy adaptive clustering hierarchy (LEACH) [2]. The former approach reports time critical data reactively, however, the later reports the periodic data proactively. Thus, continuous monitoring approach would send data to the sink even if there is no significant importance of the sensed values; the result causes the wastage of resources. To resolve these problems, a hybrid protocol has been proposed by adapting the periodic threshold-sensitive time.

The main goals of this study are to reduce the power consumption of sensor nodes and to improve data quality received by the sink node in event driven monitoring application. However, the author assumes that different nodes

detect different signal strength of the event, that is, the fault tolerances are distinct. Some sensor nodes may send packets to sink node when no event occurs due to the noise in the environment, and some sensor nodes may not send packets when an event occurs. A new thresholding technique will be introduced in this study.

Fuzziness, a feature of imperfect information, results from the lack of crisp distinction between the elements belonging and not belonging to a set. In 1969, Zadeh introduced the fuzziness/fuzzy-entropy for the first time [3], and in 1972 DE Luca and Termini introduced the axiom construction of entropy of fuzzy sets and referred to Shannon's probability entropy [4]. Due to intrinsic similarity to the equations in the Shannon entropy, fuzziness and entropy are significance of equality. It's very different from the classical entropy measure which measures probabilistic information. The index of fuzziness represents the average amount of fuzziness by measuring the distance between the sensed values. Accordingly, in this paper, based on the concept of type-2 fuzzy set, an effectively thresholding method is proposed. Given an adaptive threshold value, the membership function of a sensed value is defined by the absolute difference between the sensed value and average value. The larger the absolute difference is, the smaller the membership value becomes. In addition, the optimal threshold can then be effectively determined by minimizing the measure of fuzziness of nodes.

II. RELATED WORK

A. Event-Driven WSNs

Because the power consumption and data quality are usually the most important issues in WSNs, many research efforts have been proposed to find the best tradeoff between these two issues. Besides, in the event-driven WSNs, no event occurs at most of the time. Therefore, how to reduce the power consumption in the idle time is the another important aspect of energy saving. The authors in [5] proposed an energy efficient S-MAC protocol to arrange sensor nodes falling into sleep periodically. In [6], the authors propose an efficient sleep scheduling to exploit the timing semantics of WSNs. The proposed algorithm is light-weight because of no TDMA schedules or communication backbones needed, and the simulation results show the robust in the dynamic WSNs. In [7],

a distributed, cross layer scheduling scheme was proposed to communicate with its parent for transmission. The authors design an efficient schedule for the query processing with the following processing cycle, sampling, computing, communicating, and falling sleep. The experimental results show that the algorithm achieves the great power saving goal on the sensor nodes. In [8], the authors proposed an energy efficient protocol, multiple thresholds, and dynamic sampling/hop frequency to save energy when there is no event and wakes up the corresponding sensor nodes quickly when an event occurs.

B. Entropy and Measures of Fuzziness

The fuzziness of a fuzzy set, or entropy, tries to answer the following question: how fuzzy is a fuzzy set? Thus, De Luca and Termini first axiomatically proposed non-probabilistic entropy, they assume that E is a set-to-point mapping $E: F(2^x) \rightarrow [0,1]$, thus E is a fuzzy set defined on fuzzy universal sets [4]. Besides, if E is also satisfies the four DE Luca and Termini axioms, it is an entropy measure,

1. $E(A) = 0$ if $A \in 2^x$ (A non – fuzzy),
2. $E(A) = 1$ if $\mu_A(x_i) = 0.5$ for all i ,
3. $E(A) \leq E(B)$ if A is less fuzzy than B , i. e., if $\mu_A(x) \leq \mu_B(x)$ when $\mu_B(x) \leq 0.5$ and $\mu_A(x) \geq \mu_B(x)$ when $\mu_B(x) \geq 0.5$,
4. $E(A) = E(A^c)$.

Accordingly, there are several approaches of measuring fuzziness have been proposed, the most famous approaches are modified by Shannon's function and Yager's measuring functions [9][10]. According to the Shannon's function, De Luca and Termini defined the entropy of a fuzzy set X as

$$E(A) = \frac{1}{n \ln 2} \sum_i S(\mu_A(x_i)), \quad i = 1, 2, \dots, n$$

With the Shannon's function

$$S(\mu_A(x_i)) = -\mu_A(x_i) \ln[\mu_A(x_i)] - [1 - \mu_A(x_i)] \ln[1 - \mu_A(x_i)].$$

Using the histogram information, the above equation can be revised as [11]

$$E(A) = \frac{1}{MN \ln 2} \sum_g S(\mu_A(g)) h(g), \quad g = 1, 2, \dots, L,$$

where $h(g)$ denotes the number of occurrences at the data input level of g . On the other hand, Yager defines the major distinction between the fuzzy set and the traditional crisp set is on the discontent of the law of the excluded middle [9]. He argued that the measure of fuzziness should be dependent on the relationship between the fuzzy set A and its complement $\bar{A}$. Thus, he defined the distance between them as

$$D(A, \bar{A}) = \left[\sum_i |\mu_A(x_i) - \mu_{\bar{A}}(x_i)|^p \right]^{\frac{1}{p}}, \quad p = 1, 2, \dots,$$

where $\mu_{\bar{A}}(x_i) = 1 - \mu_A(x_i)$. The measure of fuzziness of X is denoted as

$$\eta_p(A) = 1 - \frac{D(A, \bar{A})}{|A|^{1/p}}.$$

Accordingly, to compute $D(X, \bar{X})$ can be simplified by adding the histogram information as

$$D(A, \bar{A}) = \left[\sum_g |\mu_A(g) - \mu_{\bar{A}}(g)|^p \right]^{\frac{1}{p}} h(g) \\ g = 1, 2, \dots, L.$$

Note that, for $p=1$, $D(\cdot)$ is called the Hamming metric, and for $p=2$, $D(\cdot)$ is called the Euclidean metric.

C. Type-2 Fuzzy Sets

Type-2 fuzzy sets are designed by making membership function in three dimensions where each element in type-2 fuzzy sets has membership value in range $[0, 1]$. The third dimension is an extension and adds degrees of freedom to get more information in represented fuzzy sets. Type-2 fuzzy sets are very useful when there is a difficulty in deciding appropriate membership function with ambiguity. Membership value in type-2 fuzzy sets can be any value in range $[0, 1]$. The based membership is called by primary membership, besides, related to the primary membership, there is a secondary membership by assigning possibility in range $[0, 1]$ to the primary membership. To clarify statement, the fuzzy set 'tall' is represented as

$$tall = \frac{0.95}{\text{Michael}} + \frac{0.4}{\text{Danny}} + \frac{0.6}{\text{Robert}}.$$

Conversely, the interpretation by type-2 fuzzy set could be

$$tall = \frac{\text{High}}{\text{Michael}} + \frac{\text{Low}}{\text{Danny}} + \frac{\text{Medium}}{\text{Robert}},$$

where *High*, *Low* and *Medium* are themselves fuzzy sets. The previous set is measured by one condition for one element, on the contrary, the latter defined set is measured by several conditions for one element. Type-2 fuzzy sets are useful when the exact membership for a usual fuzzy set cannot be easily determined, and hence are advantageous for incorporating uncertainties.

D. Measure of Ultrafuzziness

Accordingly to [11], to measure the threshold value as type-2 fuzzy sets is what we called "how ultrafuzzy is a fuzzy set". If membership value degree in a fuzzy set can be decided clearly and without ambiguity, then ultrafuzzy value is zero. Whenever the membership value can only state as value interval, then its ultrafuzziness total value will be increased.

Measure of ultrafuzziness $\tilde{Y}$ with L level $g \in [0, L-1]$, the histogram $h(g)$ and the membership function $\mu(g)$ can be written as follows [11],

$$\tilde{Y} = \frac{1}{N} \sum_{g=0}^{L-1} h(g) x[\mu_U(g) - \mu_L(g)]$$

where

$$\mu_U(g) = [\mu(g)]^{1/\alpha},$$

$$\mu_L(g) = [\mu(g)]^\alpha, \alpha \in [1,2].$$

Note that $\mu_U(g)$ and $\mu_L(g)$ are the upper/lower bound of fuzzy set respectively.

III. PROPOSED ALGORITHM

In this study, the author employs the network environment as the static event-driven WSN, and the approach is based on the following observations;

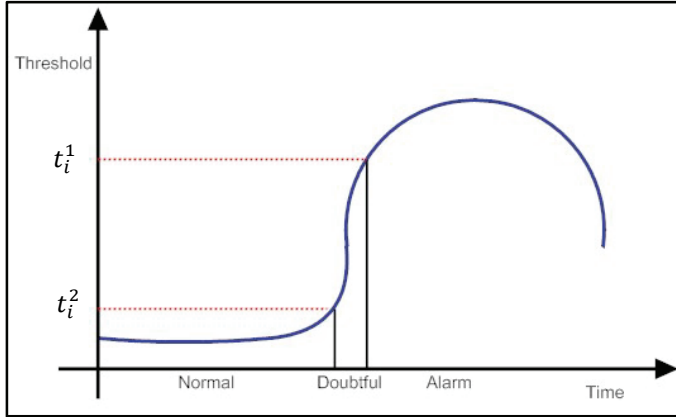


Figure 1. Multi-level thresholding

1. The sensor nodes have different quality with different signal-to-noise ratio and different memory capability, and all have limited processing and basic decision ability.
2. In some case, when an event occurs, several sensor nodes would be activated and deliver packets for response simultaneously. Thus, the network will leads to data implosion and redundancy. For the severely limited bandwidth, these nodes may have contention on the packet transmissions and ACKs overload.
3. Because of distinct signal-to-noise ratios, a sensor node with low signal-to-noise ratio may generate more irregularly data than those with high ratio when there is no event occurred.
4. With the same detected signal strength, the more sensor nodes can receive packets from sensor nodes with higher priority than ones with lower priority. In the meantime, most of retransmitted packets are redundant and useless.
5. The sink node has more resources, computation ability and memory capability.
6. For the purpose to reduce packet transmissions, each sensor node i have multiple threshold t_i^j to determine the packet need to be transmitted or not. That means that if there is no event occurred or only with noise interference, the packet don't need to be transmitted or are only transmitted to its neighbors within a small number of hops.
7. Based on the "positive feed-back" algorithm, when an event occurs, several nodes sense the varying of the

environment, the transmission hops and frequency of these nodes are also increase. Then the frequency of received packets for nodes near these sensor nodes increases, and these neighbor nodes also increase the sensing frequency too.

In this study, because of the distinct noise tolerance for each node, the author attempts to develop multi-level thresholds in the histogram of a sensor node based on the fuzziness measure, please review Figure 1. Our proposed method performs an iterative operation for each node, and we assume the target histogram contains K different non-empty data levels. The method is listed as follows;

1. Choose type of membership function to determine membership value $\mu(g)$ and initialize value of α . In this paper, three membership functions derived as the normal, doubtful and alarm states respectively.
2. Compute the history data histogram.
3. Determine initial position location of membership functions.
4. Shift membership function along data range to calculate fuzziness total in each position as shown in Figure 2.
5. Compute upper membership value $\mu_U(g)$ and lower membership value $\mu_L(g)$ in each position.
6. Calculate ultrafuzziness value for each state.
7. Compute ultrafuzziness total value with the following equation:

$$\tilde{Y}_{total} = \tilde{Y}_{normal} \times \tilde{Y}_{doubtful} \times \tilde{Y}_{alarm}.$$

8. Find the optimum threshold positions with maximum ultrafuzziness total value.
9. Threshold data using this optimum value.

Using the above method, significant differences among different states are achieved. Therefore, optimal thresholding among them can be derived.

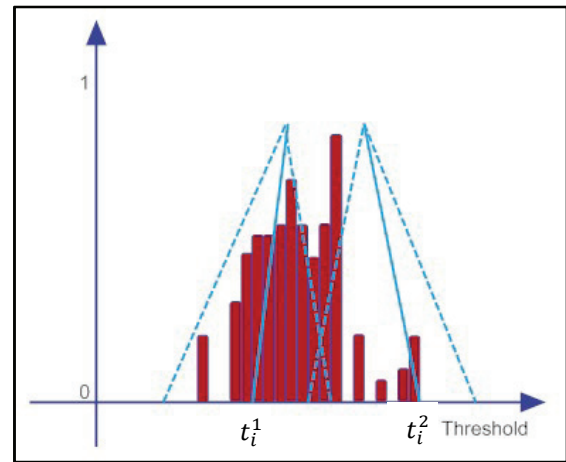


Figure 2. Shifting two membership functions

IV. RESULT AND DISCUSSION

To evaluate the performance of our method, the author simulates the transmission by TinyOS simulator TOSSIM [12]. Here real data is used for the evaluation of the techniques (Intel lab data for both sensed and network connectivity data [13]). The comparison method is the general transmission protocol to flood sensing data when nodes sense the even occurred. Figure 3 shows the average energy consumptions of our proposed protocol and general protocol over the time (1200-4000 seconds) with 20 nodes deployments. The result shows our proposed method gains the better performance than the general case. Intuitively in this case the energy efficiency is achieved on the expense of losing data accuracy.

V. CONCLUSIONS

Network lifetime is one of the most vital issues in WSNs and is fundamental to any design and development effort. Extending the lifetime of WSNs requires energy efficiency in every aspect of the utilized techniques such as energy efficient medium access control, energy efficient routing, aggregation and so on. This study presents a simple transmission technique that maintains the data accuracy while utilizing spatiotemporal correlation of data. The presented technique is to reduce the power consumption of sensor nodes and to improve data quality based on the type-2 fuzzy thresholding protocol. The potential improvement gained by using our method is demonstrated by the simulated results presented.

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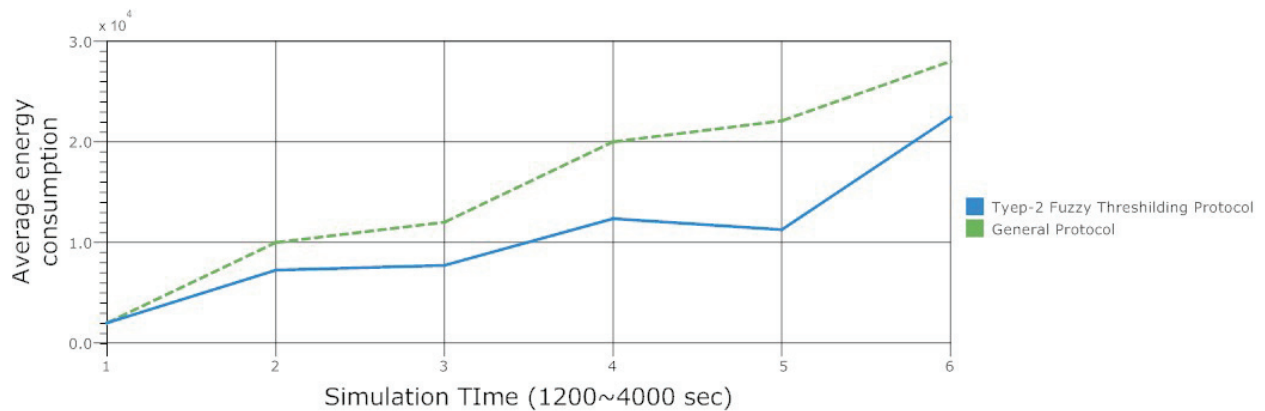


Figure 3. Performance comparison