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WSN Maximum Lifetime Combining the Heuristics Based on pERPMT

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Abstract

On account of issues such as low lifetime of WSN resulted from battery capacity limitations of sensor nodes, this paper has proposed WSN maximum lifetime algorithm combining improved heuristic method based on pERPMT. Firstly, each sensor node is initialized by heuristics, and the node energy is divided into the origin data of sensor nodes and delayed data of other nodes. Then an added preferred measure is used to delay energy consumption of one-hop node. Finally, according to the average energy of path, a priority is distributed for each routing to achieve the ultimate optimization of WSN through pERPMT. Experiments with different distribution patterns and network lifetime have verified the validity and reliability of the proposed method, and the experimental results show that compared to more advanced heuristic ERPMT-CMAX and ERPMT-OML, the proposed algorithm has significantly increased the coverage of WSN, and greatly extended the life of the network.

Keywords: WSN, MAXIMUM LIFETIME, HEURISTICS, ROUTING ENERGY MANAGEMENT, PRIORITY ROUTING ALGORITHM

Introduction

In recent years, improvements in Nano-Electromechanical System (NEMS) [1] have paved the new applications path of WSN [2,3]. WSN comprise a large number of small nodes, having capabilities of sensing, computing and wireless communication [4]. However, the battery capacity of sensor nodes is limited, resulting in its limited lifetime, and many researchers are to maximize the life of the sensor nodes through the development of new routing technologies. Therefore, to find ways to achieve energy savings and maximize lifetime is essential [5] [6]. Scholars have put forward a number of heuristics to solve the problem of network lifetime. For example, literature [7] has proposed Maximum Residual Packet Capacity (MRPC) to maximize the life of WSN, not only dependent on the remaining battery energy of nodes, but also on the expected energy dissipation of forward packets on specific connections. Literatures [8] and [9] have proposed Capacity Maximization (CMAX), and capacity is the number of routing messages within a period of time, and heuristics has provided single path (non-multipath) for each message in accordance with selection of link weights. Literatures[10] and [11] have proposed Online Maximum Lifetime (OML) method to calculate the shortest path of each message in routing. Literature[12] is to extend life by dividing the power of the node into two parts, called Efficient Routing Protocol Management Technique (ERPMT). The main problem of most heuristic energy management routing scheme is to find the minimum energy consumption route for them and to use them for each communication. However, frequent use of low-power path will lead to the energy consumption of nodes on the path, especially nodes near the sink node[13], and even when the sensor node stops running, it can lead to network segmentation [14], causing blind areas.

1. WSN Mathematical Model

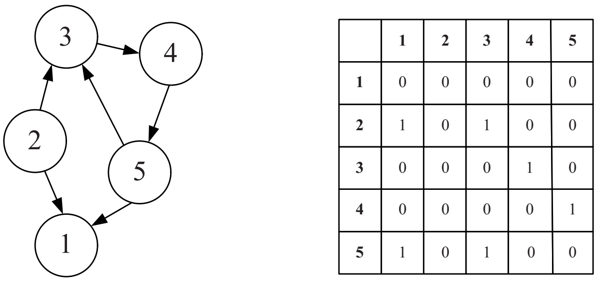
WSN can be represented by a directed graph: $G=(V,E)$, in which V represents node collection and E represents the edge-set between these nodes. If nodes u and v are within their range, there is a directed edge from node u -to-node v (such as $(v,u)\in E$). This model can be used to represent WSN. For each $(v,u)\in E$, in the single-hop transmission from sensor u to sensor v, the current energy $c_e(u)$ of sensor u may be represented by the formula (1):

$$c_e(u)=c_e(u)-w(u,v) \tag{1}$$

In the formula, $c_e(u)$ is the current energy of sensor, meeting $c_e(u)\ge w(u,v)>0$; $w(u,v)$ is the energy needed to complete the single-hop transmission from sensor u to sensor v, $w(u,v)>0$. Also assumed that the in the message-receiving process, the receiving node does not consume energy. Thus, the current energy of the sensor v is not affected by the transmission from u to v. In this paper, the energy is divided into two parts; one is the data originating node (α), and the other is the relay of other node (β). If the data is originated in the node itself, the energy from the first part will be used; otherwise it will use another part of the energy.

A adjacency matrix can be used to represent a directed graph of WSN, adjacency matrix of exact directed graph G with n vertices is $n\times n$ order matrix. When the off-diagonal digital meets $\alpha(i,j)=1$, this indicates the limbic presence from sensor i to sensor j. Diagonal figure $\alpha(i,i)$ here is set to 0, since it is assumed in this article that there is no internal circulation in the WSN.

There is only a single adjacency matrix in each figure. For example, Fig. 1 (a) shows a simple representation of sensor network S. In use of a directed graph, the represented node is sensor, side indicates that there exists edge between the sensor nodes. Figure 1 (b) shows the adjacency matrix of the sensor network S after modeling in FIG. 1 (a). Figure 1 (b) shows a network has been complete, one-dimension is used to represent sensor.



	1	2	3	4	5
1	0	0	0	0	0
2	1	0	1	0	0
3	0	0	0	1	0
4	0	0	0	0	1
5	1	0	1	0	0

(a) (b)

Figure 1. Representation of wireless sensor network: (a) Simple network diagram; (b) The corresponding adjacency matrix

2. Heuristic Priority Routing Algorithm

Scholars often use two different heuristics OF CMAX [8] [9] and OML [10] [11] to delay the lifetime of the network and access to the best life, therefore, using pERPMT and these two well known heuristics in combination.

2.1. CMAX-based Heuristic pERPMT

The first heuristic algorithm is pERPMT based on CMAX, called pERPMT_C, the improved CMAX.

Supposed the current energy of each sensor is divided into two parts, the first part is the energy supply for origin data (α)of the sensor, and the second part is the relay energy dissipation (β) of other sensors, and there are three steps for each route.

Step 1: Initialization

A sensor in each side does not have enough energy to complete the single-hop transmission and will be removed from the graph. Then the surplus for each is connected using equation (2) to assign a weight:

$$w(u,v)=w(u,v)*\left(\lambda_c^{\alpha(u)}-1\right) \tag{2}$$

In the formula, λ_c represents heuristic arguments; $a(u)$ is the percentage that has been spent on the sensor node, and it can be calculated by the formula (3):

$$a(u) = \begin{Bmatrix} 1 - c_{e1}(u)/i_e(u) \\ 1 - c_{e2}(u)/i_e(u) \end{Bmatrix} \tag{3}$$

Step 2: The shortest Path

The path in the improved chart from source node to the destination node is calculated, and if no path is found, the request fails; otherwise, it can be used unless the path is greater than certain threshold σ.

Step 3: Selection of the routing with the highest priority

The third step is to assign a priority number, size depending on the number of paths, and setting of priority series depends on the average energy of path. Furthermore, a large number of simulations shows that nodes close to the convergence node have faster energy dissipation, and therefore, these nodes are removed from the calculation. Because those nodes only one-hop away from the sink node are removed, only those paths containing at least one node within the scope of the aggregation node are selected. There is no node in the range of aggregation node, and one-hop node must be added to the calculated path.

2.2. OML-based Heuristic pERPMT

The second heuristic algorithm is pERPMT based on the OML, called pERPMT_O, assumed that the energy of each sensor is divided into two parts α, β, for each route request $r_i = (s_i, t_i)$, the following steps are performed:

Step 1: Calculate G''

All the edges in G are removed, making $c_{e1}(u)$ or $c_{e1}(u) \le w(u,v)$, as these edges requires less energy for a single transmission, the resulting figure is $G' = (V, E')$. Determination of the maximum s_i to the minimum t_i in the figure G' to is implemented through the shortest path algorithm based on Dijikstra algorithm. If there is no path from source node s to the destination node t, the routing request fails, but if the route request exists, the remaining energy is calculated using P' in formula (4):

$$\min RE = \min\{r_e(u)\ in\ P\} \tag{4}$$

Figure $G'' = (V, E'')$ can be obtained by deleting all edges (u,v) meeting $c_{e1}(u)$ or $c_{e1}(u) - w(u,v) < \min RE$ in E'. As a result, all the edges with remaining energy lower than ($\min RE$) are deleted from the figure, which can avoid the reduction in energy of low-energy sensor.

Step 2: Find route to for routing request r

Starting from G'', each edge in E'' is assigned to weight value, which has balanced requirements to minimize the total energy consumption and to avoid the energy consumption of sensor.

eMin (energy required from sensor u transmitting a message to the nearest neighbor in the figure G'') is defined as:

$$e\mathrm{Min}(u) = \min\left\{w(u,v)(u,v) \in E''\right\} \tag{5}$$

(u,v) is defined as follows:

$$\rho(u,v) = \begin{Bmatrix} 0, ifc_e(u) - w(u,v) > e\mathrm{Min}(u), u = s_i \\ 0, ifc_e(u) - w(u,v) > e\mathrm{Min}(u), u \ne s_i \\ c, others \end{Bmatrix} \tag{6}$$

In the formula, the symbol c represents a non-negative constant, an algorithm parameter. u in each u of V is defined as $a(u) = \min RE / c_{e1}(u)$ or $c_{e1}(u)$, weight $w''(u,v)$ assigned weight to each edge is calculated by the formula (7):

$$w''(u,v) = w(u,v) + \rho(u,v) * \left(\lambda_c^{a(u)} - 1\right) \tag{7}$$

In the formula, λ_c is another parameter of non-negative constant algorithm.

It can be seen that the edge on routing path is allocated with higher weight through ρ, which has reduced the remaining energy of the sensor.

Based on this, all sides with current energy distributed smaller than the sensor $\min RE$ will be assigned with high weights. Thus, the weight function prevents the use on the routing path, leading to a failure in the future route. Finally, the shortest path ρ_i'' in figure G'' is found and used for routing from s to t.

3. Experiment

Experiment is completed using MATLAB7.0, operated on 3.20G processor, 2G memory machine, the operating system of Windows XP SP3.

3.1. Parameter Settings

OML and CMAX are completed based on evenly distributed new energy management technology (ERPMT), and among the 10 networks, 20 sensors are based on uniformly distributed random deployment. Energy needed for one-hop transmission between two sensors is assumed to be $0.001 \times d^3$, and the distance between the two sensors is d. Transmission radius and initial energy of each sensor are set to 5100, and finally, c is set to, $0.001 \times r_T^3$, in which r_T is the transmission radius, and the lifetime of sensor node with first energy depletion is defined to WSN network lifetime.

3.2. Experimental Results

Simulation results show that the effect of using the energy management technology on different distribution types of network lifetime.

3.2.1. Energy Contribution of α Less Than or Equal to β.

Namely, it is the average life expectancy when $\alpha > \beta$, it is set that α can be 50%, 40%, 30%, 20% and 10%

A network of 20 sensors is randomly deployed. Figure 2 shows the average life expectancy of 10 networks of 20 sensors using methods of OML, ERPMT_O (ERPMT-based OML), pERPMT_O (pERPMT-based OML). It can be apparently seen from Figure 2that when ERPMT and OML are used in combinations, this can extend the average life expectancy in some extent, and then, since ERPMT frequently uses low-power path, leading that there exists a certain energy consumption in the path node. The proposed pERPMT can allocate a priority for each route according to the average energy of path, because nodes close to the sink nodes are energy-consuming, pERPMT can remove these nodes from the calculation, only t selecting the path with at least one node within the range of the sink node, and therefore, pERPMT and OML is combined, so that lifetime of all sensor nodes have been extended.

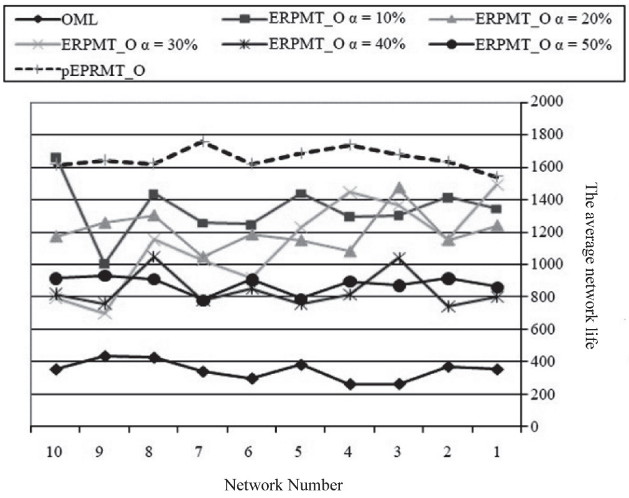


Figure 2. The average routing life of OML, ERPMT_O and pERPMT_O ($\alpha \leq \beta$)

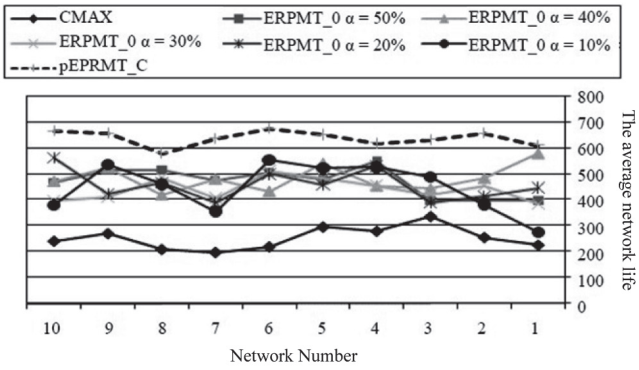


Figure 3. The average routing life of OML,ERPMT_C and pERPMT_C ($\alpha \leq \beta$)

Figure 3 shows the average routing life of CMAX, ERPMT_C and pERPMT_C ($\alpha \leq \beta$), and when using CMAX, the same law is found as in previous studies of literature [8] that CMAX has short life than OML.

3.2.2. More Energy Consumption of β Compared to α

Namely, it is the average life expectancy when $\alpha > \beta$, it is set that α can be 60%, 70%, 80%, 90%, 100%.

Figure 4 shows the average routing life of OML, ERPMT_O and pERPMT_O ($\alpha > \beta$). Obviously, with the increase in proprietary energy of data generated by sensors themselves, their lifetime tend to decline. Reduction in life expectancy is the result of increased value of α being more than 50% of the total energy, and that is, when the probability of a node finding a routing path declines, the network life expectancy decreases.

Figure 5 shows the average routing life of CMAX, ERPMT_C and pERPMT_C ($\alpha > \beta$). The same conclusion with the above results can be obtained from Figure 5 that combined use of pERPMT and CMAX can extend the network lifetime. But compared to OML method, along with changes in the value of α,

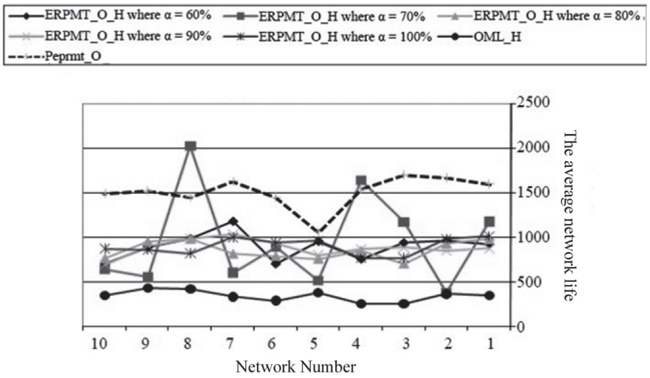


Figure 4. The average routing life of OML, ERPMT_O and pERPMT_O ($\alpha > \beta$)

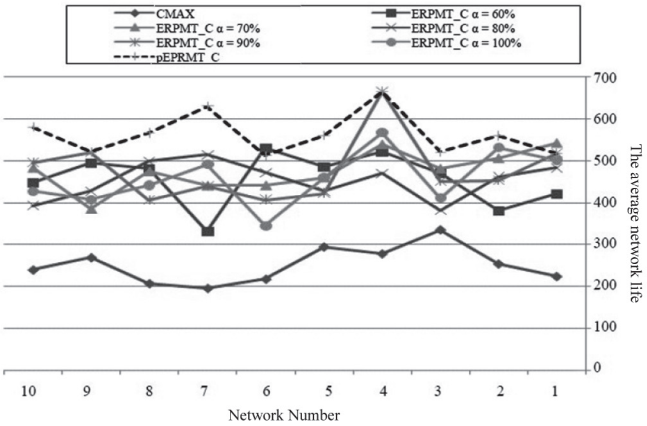


Figure 5. The average routing life of CMAX, ERPMT_C and pERPMT_C ($\alpha > \beta$)

CMAX is less impacted, for CMAX heuristics is more stable.

3.3. Comparison and Analysis

Table 1 shows the lifetime percentage difference when using OML, ERPMT_O and pERPMT_O in the formula (8). If the result is negative, then the life expectancy is reduced, or it is increase. When $\alpha \leq \beta$, life of pERPMT_O has increased 79% compared to OML.

$$\text{Percentage difference} = \frac{\text{Avg.ERPMT\_O-Avg.OML}}{\text{Avg.ERPMT\_O}} * 100\% \qquad (8)$$

Table 1. The percentage difference between proposed method and OML when $\alpha \leq \beta$

Technology	OML	pERPMT_O
Average life expectancy (seconds)	348.2	1654
Percentage difference	0	79

Technology	ERPMT_O				
	$\alpha = 50$	$\alpha = 40$	$\alpha = 30$	$\alpha = 20$	$\alpha = 10$
Average life expectancy (seconds)	878.7	840.6	1128	1205.6	1342
Percentage difference	61	59	69	71	64

Table 2 shows the percentage difference in life between CMAX and ERPMT_C. When $\alpha \leq \beta$, the life of pERPMT_C has improved 61% compared to CMAX, and ERPMT_C has improved 45% compared to CMAX.

Table 2 The percentage difference between proposed method and CMAX when $\alpha \leq \beta$

Technology	CMAX	pERPMT_C
Average life expectancy (seconds)	251.4	640.4
Percentage difference	0	61

Technology	ERPMT_C				
	$\alpha = 50$	$\alpha = 40$	$\alpha = 30$	$\alpha = 20$	$\alpha = 10$
Average life expectancy (seconds)	471.3	483.7	442.5	458.1	448.7
Percentage difference	47	48	43	45	44

Table 3 shows the percentage difference in life between OML, ERPMT_O and pERPMT_O. When $\alpha \geq \beta$, the average life expectancy of ERPMT_O has increased 61% compared to OML, and the average life expectancy of pERPMT_O has increased 76% compared to OML.

Table 3. The percentage difference between proposed method and OML when $\alpha \geq \beta$

Technology	OML	pERPMT_O
Average life expectancy (seconds)	346.2	1448
Percentage difference	0	76

Technology	ERPMT_O				
	$\alpha = 100$	$\alpha = 90$	$\alpha = 80$	$\alpha = 70$	$\alpha = 60$
Average life expectancy (seconds)	887.8	885.6	844.6	929.3	881.8
Percentage difference	61	61	59	63	61

Table 4 shows the percentage difference in life between CMAX and ERPMT_C, and pERPMT_C has improved 47% compared to CMAX, and ERPMT_C has improved 46% compared to CMAX, and subject to the stability of the CMAX methods, the percentage of life increase is considerably close to each other for pERPMT and ERPMT.

Table 4. The percentage difference between proposed method and CMAX when $\alpha \geq \beta$

Technology	CMAX	pERPMT_C
Average life expectancy (seconds)	251.4	477.6
Percentage difference	0	47

Technology	ERPMT_C				
	$\alpha = 100$	$\alpha = 90$	$\alpha = 80$	$\alpha = 70$	$\alpha = 60$
Average life expectancy (seconds)	458.3	477.6	452.7	474.8	456.3
Percentage difference	45	47	44	47	45

Based on the results, when $\alpha \geq \beta$ and $\alpha \leq \beta$ shown in Table 5, compared to the two well-known heuristics: OML and CMAX, the proposed heuristic pERPMT has increased life rate.

Table 5. Life increasing rate between ERPMT_C and ERPMT_O

Algorithm	pERPMT_C	pERPMT_C	pERPMT_O	pERPMT_O
α , β relationship	$\alpha \le \beta$	$\alpha \ge \beta$	$\alpha \le \beta$	$\alpha \ge \beta$
Life improvement rate	61%	47%	79%	76%

Clearly, when $\alpha \le \beta$, ERPMT is better than OML and CMAX, 61% and 79%. For $\alpha \le \beta$, it indicates more energy consumptions required in data transfer of other nodes compared to its own By extensive simulations using OML and CMAX, energy value of $N_1, N_2, \ldots, N_m$ hop nodes throughout the WSN lifetime can be seen, in which N_i is the i-th hop sensor node of the node; m represents the total number of nodes. Thus, the end of the WSN life is because the node only a hop away from the sink node runs out of energy. When using ERPMT, burden (eg, $N_1 < l < N_{m-1}$ in which l is the hops to rendezvous point) from forwarding aggregated data to intermediate node is converted, which is the same as the use of P_i with high priority.

Conclusions

Network lifetime problem for the lower sensor node WSN application battery capacity limit caused online On account of issues of low lifetime of WSN resulted from battery capacity limitations of sensor nodes, based on common heuristic OML and CMAX, this paper has proposed an efficient priority algorithm based on the heuristic routing energy management. Experimental results show that the algorithm has better performances in increase of network range and lifetime than the commonly used CMAX, OML and ERPMT-CMAX, ERPMT-OML. Network life still subject to many effects and must be considered in a comprehensive manner, including the dimensions of the deployment and the like. Therefore, future efforts will be made to further examine different distribution of sensor nodes and removable sink nodes in order to better improve the life and the coverage of WSN.

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Wavelet Sparse Representation based Beam-forming for Ultrasound Imaging: Theory and Simulation

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Abstract
In this paper, a wavelet sparse representation based beamforming is proposed to improve the resolution and contrast of plane wave emission ultrasound imaging. First, the received signals are described as the convolution of the target scatterers with the point spread function of the system. And then, the wavelet sparse representation model is deduced according to the fact that the target scatterers can be sparse represented in wavelet domain. The proposed algorithm was tested with simulated ultrasound data in plane wave emission. And the results demonstrated that the resolution was clearly improved and contrast ratio gains of 9.8 dB, 4.3 dB and 3.7 dB were obtained compared to delay-and-sum beamformer, minimum variance beamformer and phase coherence factor, respectively.

Keywords: WAVELET SPARSE REPRESENTATION, ADAPTIVE BEAMFORMING, PLANE WAVE EMISSION, ULTRASOUND IMAGING, IMPROVE RESOLUTION AND CONTRAST

1. Introduction

The ultrasound device with plane wave (PW) emission, because of the broad transmit beams, has the potential to achieve high-frame-rate imaging which is a key factor in the applications of real-time 3D ultrasound imaging and ultrasound cardiac imaging [1][2]. In the receiving, the array signals are conventionally processed with delay-and-sum receiving