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# Data Fusion in Wireless Communication Network Node Positioning

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**ABSTRACT**

Aiming at the problems of low localization accuracy, high energy consumption and delay of transmission in wireless sensor networks, a wireless sensor network data fusion method is proposed. Combined with the theory of D-S argument, the wireless sensor network system model is first constructed. Then based on the analysis of ACO (Ant Colony Optimization) and MST (Minimum Spanning Tree) methods, a wireless sensor network data fusion method is proposed. The simulation results show that the larger the number of nodes in WSN is, the larger the energy consumption and delay are. As the moving speed of Sink node increases, the average transmission delay decreases and the useful data rate increases. The average energy The consumption is also gradually increasing; the performance of proposed WSN data fusion method is better than that of ACO and MST.

***Keywords**:* data fusion; algorithm design; mathematics modeling; wireless sensor network

## 1 Introduction

Wireless Sensor Network (WSN) is a distributed sensor network. It is a multi-hop self-organizing network formed by wireless communication. WSN can achieve target positioning. However, its positioning accuracy is the main indicator to measure the performance of WSN. Therefore, how to improve the positioning accuracy of WSN nodes is a key issue and a problem. WSN data fusion is one of the techniques to improve positioning accuracy.

The WSN is generally a single source node with multiple source nodes. This model can generally be regarded as the minimum Steiner Tree (MST) problem of covering the source node and the sink aggregation node [1-3]. The WSN data fusion algorithm is currently based on the traditional client/server (C/S) model. In this model, the sensor node is regarded as a Client, and the Sink node is regarded as a Server. The Sink node collects data transmitted from each sensor node according to a routing protocol, and performs centralized fusion processing. For

WSN, there are many problems in the C/S model [4-7]: (1) Network delay and energy consumption are large. Each sensor node can transmit data to the processing node at the same time, and the processing node can only receive the data sequentially. When the number of sensor nodes increases and the total amount of sensing data increases, the network delay and energy consumption increase. (2) Poor scalability. When the WSN supplements new sensor nodes, the network structure often needs to be

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adjusted to maintain load balancing. (3) Node energy consumption is not balanced. Because the processing node needs to maintain the connection with each sensor node and process its data, it consumes more energy than the sensor node. This requires the node with preset super energy as the processing node or some algorithm to rotate the processing node, adding extra network overhead.

With the introduction of the mobile agent (Mobile Agent, MA)-based computing model in WSN, the problems caused by the traditional C/S model are solved to some extent [8-12]. In the WSN data fusion, the MA computing model is used, that is, the sensing data is kept locally at the node, and the MA is migrated to the data, and the appropriate algorithm is used for the fusion processing. The essence is to "move the fusion computing to the data", which enables It overcomes the shortcomings of traditional data fusion algorithms, reduces network bandwidth requirements, reduces energy consumption and delay, and enhances network stability while achieving better data fusion effects. After the MA-based data fusion is closely integrated with the routing strategy of the MA, it can effectively alleviate network congestion during data aggregation and ultimately prolong the network lifetime [13-15].

Diego V. et al. [15-16] proposed a multi-agent data fusion method based on the mobile-agent approach. The method has improved the energy elimination node reaction time and network lifetime. Habib M et al. [17-20] combined the static WSN with the dynamic WSN to analyze the complexity of node data fusion. First, define the boundary of the node in the static network, and then construct the topology domain of the dynamic network. Finally, the data fusion of the nodes is carried out according to the evolution graph. Sadia Din et al. [21-25] overcome the traditional single Sink deficiency based on practical applications. The multi-Sink node processing method of WSN is proposed, and the routing algorithm of multiple Sink nodes is proposed. M. Z. Zambian et al. [26-27] proposed a new energy-efficient structural data fusion protocol based on the energy consumption of the transmitted data, which consumes too much energy compared to the local data processing of the node. The simulation of the proposed data fusion protocol in energy consumption, reliability, the timeliness of data transmission has obvious advantages over traditional methods.

## 2 Data Fusion Mechanism and Method

There are three main data fusion mechanisms for WSN nodes: Tree-based, Cluster-based, and Centralized-based [27-28]. As can be shown in Fig.1.

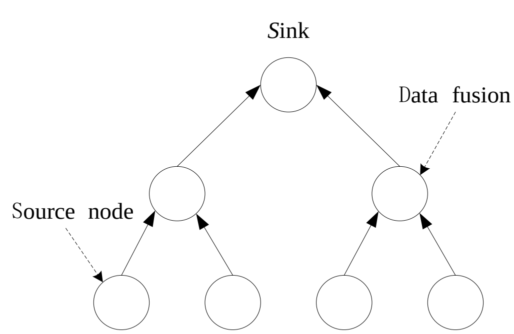


**Fig.1 Tree-based data fusion**

In Fig.1, there is a Sink node multi-source node situation. The node fuses the sensing data of multiple source nodes, and then transmits the merged data to the Sink node [29-31].

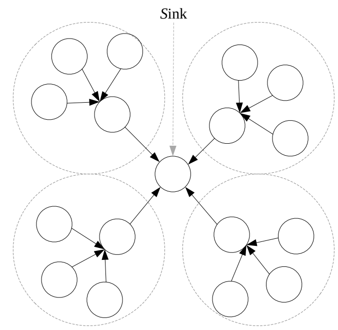


**Fig.2 Cluster-type data fusion**

In Fig.2, a clustering method is also a multi-source single-sink case. Each cluster contains multiple source nodes and one head node, and data fusion is performed at the head node. The data perceived by each source node is fused at the head node according to a certain data processing algorithm [32-37]. Each head node then transfers the merged data to the Sink node.

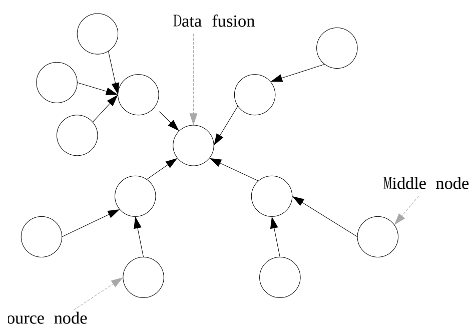


**Fig.3 Centralized-based data fusion**

In Fig.3, there is a central method. The model contains multiple branches. Each branch contains multiple source nodes and intermediate nodes. The data sensed by each branch node is transmitted to the head node and merged according to the data fusion mechanism and method.

Different fusion methods can be used for the perceived data. If there is complementary fusion, redundant fusion, cooperative fusion and other methods to analyze and process the event information, as shown in Fig.4[26-28].

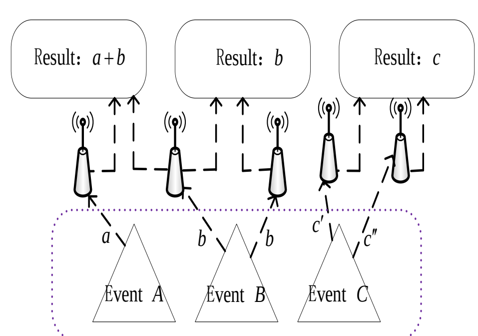


**Fig.4 Data fusion based on time information source**

# 3 Data Fusion Algorithm

## 3.1 Traditional methods

*(1) ACO*

The ACO algorithm adopts distributed parallel computer system and has strong robustness. The essence of the ACO algorithm optimization process is that the path with the larger amount of information has a higher probability of being selected; the amount of information above the path grows with the passage of ants and also decreases over time; the ants actually communicate and work together through the amount of information. Such a mechanism makes the ant colony algorithm have a strong ability to find better solutions.

*(2) MST*

The MST algorithm requires $n-1$ edges to be selected from a weighted undirected complete graph and the graph is still connected (that is, a spanning tree is obtained), and the weight of the tree is also considered to be minimized. The main idea is: First, use a node as the initial node of the minimum spanning tree. Then iteratively find the minimum edge with the weight of each node in the minimum spanning tree, and added to the minimum spanning tree. If a loop is generated after the join, skip this edge and select the next node. Once all the nodes have been added to the minimum spanning tree, the smallest spanning tree in the connected graph is found.

## 3.2 D-S argument theory

Dempster-Shafer (D-S) argumentation theory [18-20] can nonlinearly integrate data collected by different WSN sensing nodes. Dempster-Shafer theory can be applied in statistics, big data, information statistics and other related fields, and got a good development.

There are two trust function $Bel_1$ and $Bel_2$ under the same $\Theta$, $m_1$ and $m_2$ are their credibility assignments. The focus elements of both are $A_1, A_2, \cdots, A_K$ and $B_1, B_2, \cdots, B_K$. Then the Dempster merge rule can be expressed as:

$$m(C)=\begin{cases} 0 & C=\varnothing \\ \dfrac{\sum_{i,j=1}^{n} m(B)_i m(A)_j}{1-K} & \forall C \subset U, C \neq \varnothing, A \cap B = \varnothing \end{cases} \tag{1}$$

In the above formula, $K$ is a normalization constant. And the following formula is satisfied.

$$K=\sum_{i,j=1}^{n} m(B)_i m(A)_j < 1 \tag{2}$$

In the formula $K \neq 1$, then $m$ determines a basic probability assignment, indicating that the two sets of information $m_1$ and $m_2$ are identical or only partial information conflicts. The introduction of the canonical number $K$ is actually to add the orthogonal and proportional proportions discarded by the empty set to the non-empty set, and make the $m(C)$ still satisfied:

$$\sum_{C \leq \varnothing}^{n} m(C) = 1 \tag{3}$$

When D-S reasoning is used for data fusion of multiple WSN nodes, each node collects target information. Through D-S theory for data fusion, the feature vector of the target information can be calculated, so that accurate positioning can be achieved.

### 3.3 Node data fusion method

In the wireless sensing area, different sensing nodes are distributed, and the influence factor $I_{jk}$ between two different sensing nodes $j$ and $k$ can be expressed as:

$$I_{jk} = e^2 \frac{-(H_j^k - 1)^2}{3\sigma^2} \tag{4}$$

Where, $\sigma$ is the influence extent between $j$ and $k$. $H_j^k$ is the estimated hops between $j$ and $k$. Which can be expressed as:

$$H_j^k = \frac{d^2(l-1, l)}{R_{\max}} \tag{5}$$

Where, $R_{\max}$ is the max transmission distance.

In communication area, The amount of energy $E$ of a node during a data acquisition cycle is:

$$E = \eta h_{si} P_s t_s + \lambda \sum_{j \in N}^{n} \eta h_{ji} P_j t \tag{6}$$

Where, $\lambda$ is the random modify variable, $0 \le i \le 1$, $0 < \eta < 1$ is energy conversion coefficient. $h_{si}$ and $h_{ji}$ is the wireless communication link gain between different nodes. $t_s$ denotes the time slot. $P_s$ is the power of sink node. $P_j$ is the transmit power of node $j$. Node energy consumption $E_{consume}$ can be denoted as

$$E_{consume} = v_i \varepsilon + \sum_{k=0}^{n} v_k e + P_i t \tag{7}$$

Where, $\varepsilon$ and $e$ is the unit energy consumption. Is the transmit power of node $i$. $v_i$ and $v_k$ is the amount of data collected at different nodes.

According to Shannon Formula:

$$C = B \log_2 (1 + \frac{S}{N}) \tag{8}$$

It can be concluded that the maximum data transmission rate of a node in the WSN area is:

$$\zeta_i = B \log_2 (1 + \frac{P_i h_{id}^{\ 2}}{\delta_{id}^3}) \tag{9}$$

In equation (9), $\delta_{id}$ is the noise power between two different nodes, and $h_{id}$ is the link gain between two different nodes. $B$ is the bandwidth of the wireless communication channel.

In the wireless communication sensing area, it takes a certain amount of time to complete a round of data collection. The average time interval required to complete a round of data collection can be expressed as:

$$T = \varepsilon \frac{\sum_{i=1}^{r} \max_{1 \le j \le k} \{T_{i,j}\}}{r} \tag{10}$$

Where, $\varepsilon$ obey the power law function distribution. $r$ is the number of data acquisition rounds for data fusion in the communication network, and $k$ is the number of proxy nodes.

It is assumed that the wireless communication channel bandwidth of the communication network is B(b/s), the time at which the proxy node transmits the data packet can be expressed as:

$$T_{\text{packet}} = \varepsilon \sum_{i=1}^{n} (T_{proc} + ((S_{ini}{}^{2} + \frac{i \cdot d}{2}) / B) + T_{prop}) \tag{11}$$

Where, $T_{proc}$ is the time it takes for a proxy node to complete data fusion, and is a constant; $S_{ini}$ represents the amount of data packets of the Sink node; $T_{prop}$ is the transmission time of the node, mainly based on environmental factors such as the actual transmission distance of the WSN area

## 4 Simulation Analysis

There are 439 nodes in the sensing area $600 \times 600\, m^2$, the initial node energy is 50J, and 50 bytes per package. The bandwidth is 30Kb/s. It is simulated and analyzed based on D-S theory.

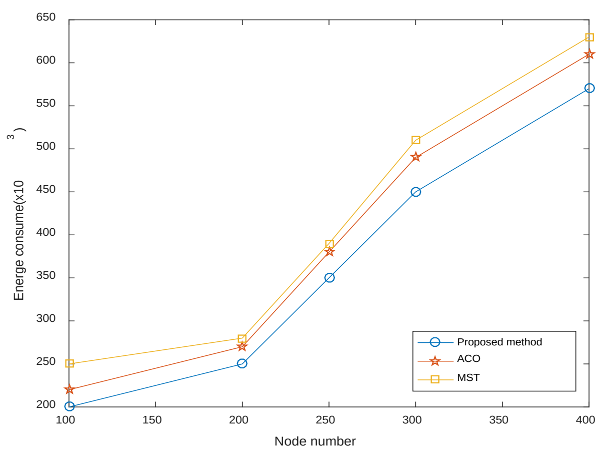


**Fig.5 Energy consumption and network nodes**

It can be seen from Fig.5 that as the number of network nodes increases, the energy consumption increases gradually. In the case of the same number of nodes, the energy consumption of this method is smaller than the other two traditional methods.

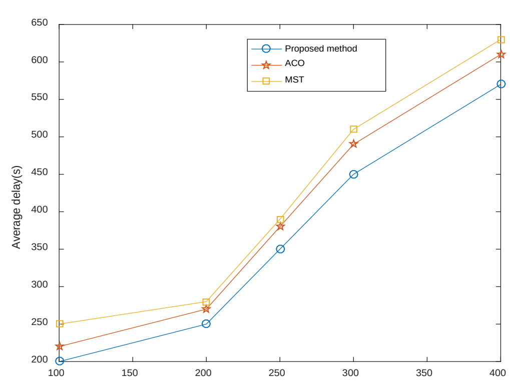


**Fig.6 Average delay and node relationship**

It can be seen from Fig.6 that as the number of WSN nodes increases, the average delay is on the rise. In the case of the same number of nodes, the average delay of the method in this paper is smaller than ACO and MST.

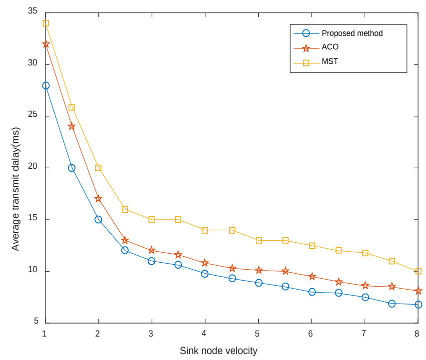


**Fig.7 Transmission delay and Sink speed**

It can be seen from Fig.7 that as the speed of the Sink node increases, the average transmission delay tends to decrease, and the average transmission delay of the Sink node decreases from 1 to 2.5. But the Sink node speed changes from 2.5 to 8 in the same number of nodes, the average transmission delay is slower, but the transmission delay is still slower. It can be seen that the average delay of the method herein is smaller than ACO and MST.

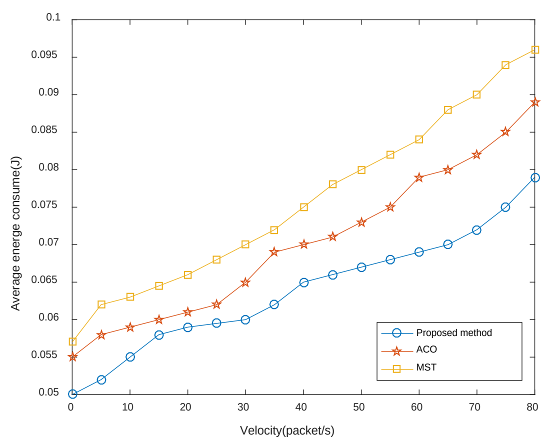


**Fig.8 Data rate and energy consumption**

It can be seen from Fig.8 that as the data rate increases, the average energy consumption increases gradually. In the case of the same data rate, the energy consumption of this method is smaller than the other two traditional methods.

## 5 Summary

After analyzing the data fusion mechanism of WSN, the system model of WSN is constructed. A data fusion method based on the theory of D-S argumentation is proposed. Consider the energy consumption and time delay in different node numbers, data rates, and so on. The simulation results show that the larger the number of nodes, the greater the energy consumption and delay. The larger the Sink node's moving rate is, the smaller the delay is. It can be concluded that the performance of this method is better than ACO and MST. The key technical issues to be studied in the next step are: the relationship between the node energy consumption of WSN and the node density and speed and the node dynamic topology model in the case of a specific total number of nodes.

## AUTHOR CONTRIBUTIONS

The authors performed the experiments and analyzed the results together. Introduction, methodology, cosmetic detection algorithms and proposed model have been written by Xiaoyang Liu; while data collection, experimental results and conclusion sections have been written by Ya Luo and Chao Liu.

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