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Two-Tier Cooperation Based High-Reliable and Lightweight Forwarding Strategy in Heterogeneous WBAN

Jirui Li [1,†], Junsheng Xiao [1] and Jie Yuan [2,*,†]

1 School of Information Technology, Henan University of Chinese Medicine, Zhengzhou 450046, China
2 Key Laboratory of Trustworthy Distributed Computing and Service, Beijing University of Posts and Telecommunications, Beijing 100876, China
* Correspondence: yuanjie@bupt.edu.cn
† These authors contributed equally to this work.

Abstract: Due to the limited and difficult access to sensor energy, energy conservation has always been an important issue in wireless body area network (WBAN). How to make full use of the limited energy of heterogeneous sensors in WBAN to achieve lightweight and high-reliable data transmission has also become key to the sustainable development of telemedicine services. This paper proposes a two-tier cooperation based high-reliable and lightweight forwarding (TTCF) mechanism via minimizing the amount of transmitted data and optimizing forwarding performance, so as to improve the efficiency and reliability of WBAN and reduce system energy consumption. In TTCF, an adaptive semi-tensor product compressed sensing evolution (STPCSE) model is first constructed to minimize the amount of data to be transmitted and extend the lifetime of sensors. Then, the important factors closely related to the energy consumption of human body sensors, including sampling frequency, residual energy and their importance in the network, are analyzed and redefined, and a high-reliable and lightweight forwarding model based on a multi-factor dynamic fusion is built. Finally, the performance and energy-saving effect of TTCF in a dynamic WBAN environment are compared and analyzed. Simulation results show that the system with our TTCF always performs the best in terms of data reconstruct accuracy, cumulative delivery rata, energy consumption and throughput. For example, its cumulative delivery rate is about 12% and 20.8% higher than that of UC-MPRP and CRPBA, and its residual energy and throughput are 1.22 times and 1.41 times, 1.35 times and 1.6 times of the latter two, respectively.

Keywords: data forwarding; energy efficiency; heterogeneity; high-reliable; lightweight; wireless body area network

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Citation: Li, J.; Xiao, J.; Yuan, J. Two-Tier Cooperation Based High-Reliable and Lightweight Forwarding Strategy in Heterogeneous WBAN. *Sustainability* **2023**, *15*, 5588. https://doi.org/10.3390/su15065588

Academic Editor: Manuel Fernandez-Veiga

Received: 8 February 2023
Revised: 15 March 2023
Accepted: 20 March 2023
Published: 22 March 2023

1. Introduction

WBAN is essentially a human body centered wireless sensor network, which has the function of an ad hoc network [1]. Based on WBAN technologies, real-time, convenient and all-weather health monitoring for patients' physical condition can be realized by arranging heterogeneous sensors on a patient's body surface or body that can automatically collect vital sign parameters such as electrocardiograms (ECG), electroencephalograms (EEG), electromyography (EMG), body temperature, blood pressure, blood glucose and blood oxygen [2]. The data in WBAN is often transmitted through multiple hops, and intermediate nodes need to undertake the forwarding tasks of other nodes. However, because each node of WBAN is generally powered by a micro battery, very limited energy is carried by each node and there is a high sensor replacement cost. Meanwhile, slight changes in human posture (e.g., standing, sitting, lying and walking), energy acquisition or the depletion of sensor nodes, and shadow parts of human body, etc., will affect frequent changes in the topology structure and wireless link status of WBAN, resulting in a higher energy consumption of WBAN services. Therefore, as people pay more and more attention to their health and continue to pursue high-quality medical services, how to effectively use the limited energy of sensors to improve the efficiency of WBAN data transmission is still a major challenge faced by researchers.

Many studies [3–14] were conducted in an effort to realize energy saving and efficiency improvement for WBAN data transmission by using various methods or technologies, such as developing new energy-saving sensors [3,4], enhancing the performance of existed data transmission schemes [5–7], improving channel environment [8–10] or compressing the amount of data to be transmitted [11–14]. Usually, most studies adopted one of the above methods to improve the quality of services (QoS) of WBAN. However, it is too ideal because it requires multiple technologies to cooperate simultaneously to efficiently complete WBAN data transmission. It is obvious that the development of new energy-saving sensors and the improvement of the channel environment are usually achieved by improving the technical performance of hardware. From the perspective of improving the performance of soft applications, the combination of new data compression methods and new forwarding models will also effectively improve the efficiency of WBAN data transmission.

Compressed sensing technology can compress the original data signal in low dimensional space by using the sparsity of the sampled signal to reduce the amount of data to be transmitted [15], and can also use nonlinear algorithm to finish the precise reconstruction of sparse or compressible signals. Although the literatures [11,16,17] have proposed various new compressed sensing methods or models for reducing energy consumption in WBAN, they all have certain limitations because they cannot solve the problem of the inconsistent dimensions of the parameter matrices caused by the heterogeneity of medical data. A semi-tensor product [18] is an extension of traditional matrix multiplication. It not only meets all the characteristics of matrix multiplication, but also can be used when the dimensions of matrix multiplication do not match. STPCS uses a semi-tensor measurement matrix based on compressed sensing. It retains the feature that compressed sensing can compress and encrypt at the same time, and greatly reduces the size of the measurement matrix. Xie Dong et al. [19] have proved that STPCS conforms to Spark, cross-correlation and constrained isometric characteristics, and meets the conditions for accurate signal reconstruction. Zhang et al. [20] proposed the compressed sensing of EEG signals to ensure low energy consumption and cheap hardware. The literatures [21–24] also improved STPCS to reduce the energy consumption of computation and storage while transmitting medical images or data. Obviously, it is feasible and necessary to use STPCS to compress data before transmission.

Improving the forwarding performance of medical data after compression can further raise the reliability of data transmission and reduce network energy consumption. Traditional network routing algorithms often chose the path with the least hops between the sink node and source node to transmit data. However, for WBAN, because the energy of each node is very limited, the repeated use of the same path to transmit data information for many times will cause the nodes on this path to consume too much energy, so they will die prematurely. Due to the premature withdrawal of nodes, the original network as a whole has become fragmented and independent of each other, shortening the life cycle of the whole network. Dynamic routing algorithms based on a multi-path mechanism can effectively solve the above problems. This kind of algorithm usually establishes multiple paths between the sink node and source node, and then selects the path with the largest sum of the minimum residual energy of the nodes for data transmission, according to the residual energy between the nodes on the paths [25]. Compared with single path transmission algorithms, although multi-path algorithms can significantly improve the life cycle of the whole network, node residual energy is not the only factor that can determine the forwarding capacity of nodes and the energy-saving effect of the network. For example, sensors that undertake different businesses generally have different sampling frequencies, and sensors with high sampling frequency in WBAN are mostly used to collect data, and are not suitable to participate in forwarding tasks as relay nodes [7]. Due to the particularity of medical applications, some data collection can be completed soon, but there is still energy in these collection nodes, which can provide data forwarding services for other nodes. Giving priority to the use of their residual energy and using this residual energy as early as possible can also be considered in the design of the data forwarding model [26]. In addition, there are many kinds of business data collected by WBAN medical sensors, some of which are crucial and must be guaranteed at all times, such as ECG and blood pressure. Some can be interrupted or delayed, such as body temperature and current video information. Even some nodes only have a forwarding function, but not a collection function. Obviously, according to these characteristics, defining the important position of a node in network data transmission based on the importance of collecting data or the frequency of providing forwarding services can be another decisive factor in selecting relay nodes [27]. Thus, on the basis of a multi-path mechanism, fully and comprehensively considering to select many main factors that affect the energy consumption of nodes or networks to measure the forwarding ability of nodes will ensure that the forwarding model is established closer to the actual needs.

Given all of that, for the dynamic environment of WBAN caused by the irregular movement of human limbs or the gain and loss of sensor energy, how to select appropriate factors and methods to construct a high-reliable and lightweight data forwarding mechanism is very important. This paper proposes a two-tier cooperation forwarding (TTCF) mechanism to achieve the above goal, and its major contributions are as follows:

- *TTCF leverages the STPCSE model to compress heterogeneous medical data in WBAN and solve dimension mismatch in large matrix multiplication during compression and reconstruction, so as to reduce network redundancy and the amount of data to be transmitted, cut down system energy consumption and improve forwarding efficiency.*
- *TTCF measures the forwarding ability of sensor nodes by combining sampling frequency, residual energy and their important status in the network to the Entropy Weight (EW) method [28], and uses Euclidean distance to calculate the short-distance spatial transmission energy consumption between them, and then leverages the linear weighted sum of the two as the forwarding utility to measure the comprehensive ability of nodes. It not only ensures the objectivity of relay node selection as much as possible, but also further takes into account system energy consumption.*
- *On the premise of making full use of the nodes that are about to exit the network, TTCF integrates the forwarding utility of measuring the comprehensive ability of nodes into Dijkstra algorithm to effectively improve the calculation of the data transmission path, and is evaluated on a simulation scenario based on a human body containing different types of sensors. Experimental results show that TTCF always exhibits better performance in terms of data reconstruction, energy consumption and throughput control. For example, its cumulative delivery rate is about 12% and 20.8% higher than that of UC-MPRP [29] and CRPBA [30], and itsresidual energy and throughput are 1.22 times and 1.41 times, 1.35 times and 1.6 times of the latter two, respectively.*

The rest of the paper is organized as follows: Section 2 reviews the related work. Section 3 introduces the implementation of the TTCF strategy, including the STPCSE model, the measurement method of relay nodes, the forwarding utility, the improved Dijkstra algorithm and the TTCF rule and algorithm. Section 4 builds the simulation environment and gives the experimental parameters and performance analysis for TTCF. The existing problems and future work are discussed briefly in Section 5, and Section 6 concludes the paper.

2. Related Work

WBAN sensor nodes are portable and have the characteristics of small size, light weight, limited energy, inconvenient battery replacement and so on. The dynamic behavior of human limbs maybe due to the communication interruption that is the main cause of the data route reconstruction and retransmission and the reconstruction of network topology. Obviously, energy limitation is an important problem in WBAN, and the research on the lightweight data forwarding mechanism for WBAN will be the basic work to achieve energy-efficient telemedicine services.

The data sent by WBAN nodes has a certain continuity and correlation, which represents redundant information. Thus, it is necessary to remove data redundant information to reduce the amount of data sent in the applications, which not only saves a lot of energy, but also reduces network transmission congestion, the transmission delay of data and the conflict when these data are sent, and improves the utilization of wireless channels. Apparently, the energy consumption of WBAN data forwarding mainly depends on the amount of data transmitted by the network and the selection of relay nodes [31].

Abidi et al. [16] applied compressed sensing theory to WBAN and proposed a new distributed compressed sensing reconstruction algorithm to effectively reduce node power consumption. Mondal et al. [17] applied sparse representation theory and compressed sensing theory to data compression and action number recognition in human activity detection [32–35], so as to reduce energy consumption in the network as much as possible when a specific action recognition rate is achieved. Shoaib et al. [21] put forward a method of capturing and detecting EEG based on compressed sensing, which reduces the energy consumption of communication and computing. However, the traditional data compression sensing technology has strict restrictions on the dimension of signal matrices, which is not conducive to dealing with ubiquitous heterogeneous medical signals. Peng et al. [36] proposed an STPCS algorithm to save computing resources, and applied it to the communication of wireless sensor networks. Ping et al. [23] leveraged STPCS to reduce computational and spatial resources when designing a visually secure image encryption scheme. Peng et al. [37] proposed a P tensor product (PTP) based on STPCS. The selection of matrix P is unlimited and can be any kind of matrix. It not only solves the problem of dimension matching in matrix multiplication, but also provides a new method for calculating the angle between different dimensional vectors. Based on PTP, Xiao et al. [24] solved dimension matching in the multiplication between large measurements matrices and greatly saved the storage consumption of image encryption. Obviously, the model based on STPCS not only inherits the advantages of compressed sensing, but also overcomes the dimension limitation of matrix multiplication. Applying STPCS to WBAN data forwarding can solve the problems of adaptability, energy, security and so on.

In addition, the performance of data forwarding is directly related to the efficiency and energy consumption of the network. In most applications of WBAN, data may be transmitted to target nodes through multi-hop routing. Natarajan et al. [38] showed that it was feasible to use relay nodes to realize multi-hop data transmission in the human body network, which can greatly improve the robustness of communication between nodes. However, the design of the multi-hop routing mechanism in the human body network has not been explored to a great extent. Nadeem et al. [39] proposed that the human body relay sensor could cooperate with other nodes of the body to perform the corresponding forwarding operation to achieve smooth data transmission. Liang et al. [40] also showed that the selection of sensor relays would affect the energy consumption and network connection of the human body network [41]. Therefore, data transmission in practical human body network applications can be achieved by cooperating with the energy cost of sensor relays [42]. In this cooperative data transmission, the energy consumption of relay sensors is very high, which will inevitably lead to the imbalance of sensor energy consumption, and the literatures [43–46] provided some corresponding data forwarding measures for this problem. Guo et al. [47] and Roy et al. [48] designed WBAN forwarding methods according to the energy consumed by the link when sensor nodes transmitted data. However, due to the existence of too many assumptions and strong constraints, some subjective one-sidedness exists in their proposed methods. For the sake of objectivity, the literatures [49–51] have designed or improved data forwarding schemes based on factors such as the residual energy of sensor nodes. Umare et al. [52] proposed an optimization scheme of WBAN routing protocol based on clustering using the genetic heuristic method, and used the genetic algorithm to determine network energy consumption, so as to prolong network service life. Ibrahim et al. [53] built a minimum cost function for WBAN to select the forwarding node with the largest residual energy and the shortest distance, and proposed an emergency data transmission protocol based on an enhanced energy-saving threshold.

Although the above studies improved the performance of WBAN data transmission to some extent, they ignored a key premise, that is, WBAN sensors are heterogeneous, and their energy consumption rates are different [54,55]. Therefore, only using initial energy and residual energy cannot accurately describe the heterogeneity of sensors. The main reason is that the importance of data collected by different sensors is also different, and the residual energy of important sensors must be maintained at a high enough level to deal with emergencies. Moreover, in the past, most energy-saving studies on WBAN data forwarding only focused on the performance improvement of the forwarding model, and obviously ignored the impact of de-redundancy processing on system energy consumption before forwarding, even though the data de-redundancy or compression technology has been very mature. That is to say, the design of the preprocessing and forwarding mechanism of data to be transmitted has not formed a systematic model in WBAN data forwarding and related studies. Therefore, for the dynamic WBAN environment, this paper will improve the efficiency of data transmission and reduce the energy consumption of the system by cutting down the amount of data to be transmitted and raising the forwarding performance.

3. Two-Tier Collaboration Based High-Reliable and Lightweight Forwarding (TTCF) Mechanism for WBAN

In the field of information technology, high availability refers to a system or component whose running time can meet the expected time [56]. The less time it takes to efficiently and accurately transmit data to the target node within the expected time, the higher the reliability of the data forwarding operation. The efficiency of the data forwarding operation is directly related to the size of the forwarding data itself and the performance of the forwarding algorithm. The smaller the amount of data transmitted, the less energy is consumed to transmit the same data. The faster the forwarding algorithm runs and the higher the accuracy of the results, the higher the efficiency of the data transmission and the more reliable the data forwarding is. Therefore, this paper proposes the TTCF model, which intends to improve the problems of low reliability and high energy consumption in the existing research by reducing the amount of data transmitted and improving the efficiency and accuracy of the forwarding.

The design and implementation of TTCF is shown in Figure 1.

In Figure 1, the bottom part represents various types of sensing devices, which are mainly responsible for identifying various physical objects and collecting WBAN context and indicator data, such as ECG, EEG, EMG, medical imaging and other heterogeneous data. The top layer is a variety of smart devices that act as data sink nodes, such as mobile phones, computers, vehicles, etc., which are mainly responsible for calculating, storing, analyzing and providing feedback on the collected data, or transmitting it to more powerful network devices for further processing. The middle part is the TTCF strategy proposed in this paper. Data is measured from the individual and its surrounding environment through small sensors, embedded systems, RFID tags and readers, small and medium-sized to large diagnostic and healthcare equipment, medical and clinical imaging equipment and any sensing equipment that supports data acquisition and transmission, and is then transmitted to the corresponding sink node through the TTCF strategy running in a heterogeneous WBAN environment.

The TTCF strategy includes two parts: the STPCSE model and the forwarding model based on multi attributes and improved Dijkstra algorithm. The former mainly leverages the STPCS model to develop a new and more powerful data compression model which can use the same measurement matrix to measure signals of various lengths, and can compress various data by reducing the number of rows and columns of the measurement matrix, thus effectively reducing the amount of data transmission, improving the forwarding efficiency and saving the energy of the WBAN. The latter focuses on the improvement of the performance and reliability of the forwarding model. It firstly leverages multiple attributes closely related to nodes and the energy consumption between two nodes to measure the forwarding ability of the encounter nodes, and then uses the improved Dijkstra algorithm to compute the shortest path between the source-goal nodes based on the above forwarding ability measurement values. TTCF makes every effort to improve the correctness and efficiency of each step of forwarding to ensure the reliability of data transmission.

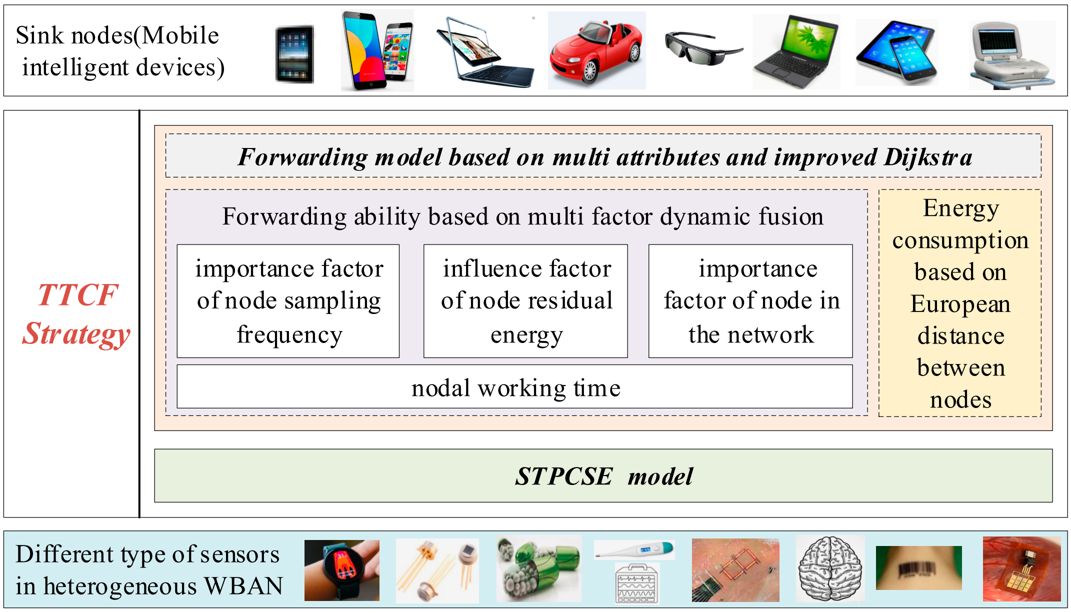


Figure 1. TTCF strategy in heterogeneous WBAN.

Moreover, because each node in the actual WBAN application needs to be powered by batteries, and most of the nodes are relatively static, the proposed TTCF algorithm follows the following preconditions:

- Compress data on nodes adaptively before transmission based on the correlation between them.
- Each node is relatively static, and the sink node receives data information transmitted by other nodes.
- In WBAN, the energy of the sink node is infinite, and the initial energy, data rate and sampling frequency of the other nodes are assigned according to the type of sensor.
- The node status is classified according to the importance of its collected data.
- After each round of communication, each node calculates the current residual energy value.

For ease of reading, the symbols and meanings of the main variables in this paper are given in Nomenclature part. The main solutions and related key technologies are as follows.

3.1. STPCSE Model in TTCF

The online compression of perceptual data to reduce the amount of transmission and storage is one of the means to achieve energy saving in WBAN. Therefore, compression methods need to meet the requirements, such as a fast compression speed, large compression ratio, easy hardware implementation, less resource consumption and high reconstruction accuracy. Common monitoring data compression methods include LZW (Lemplel-Ziv-Welch) lossless compression algorithm, wavelet compression, Huffman coding compression, neural network compression, etc., which are based on the characteristics of perceptual data, and achieve data compression by using some means to remove the redundancy of perceptual data. Such compression often needs to design complex compression coding algorithms, which is difficult and time-consuming to implement in an embedded environment. WBAN online data compression expects that the compression process will be as convenient as possible, but the requirements for decompression speed are not strict, which can be completed on the computer offline. In other words, it hopes to find a new algorithm that can separate the complex operation process from the coding.

Although the emergence of compressed sensing makes it possible to solve these problems, traditional compressed sensing methods require that the number of columns of the measurement matrix should be equal to the number of rows of the signal when using matrix multiplication, which makes the measurement matrix occupy more memory and have high computational complexity in the practical applications. The STPCS method is a generalized adaptive online compressed sensing technology. It overcomes the limitation of consistent dimension when the measurement matrix is multiplied in traditional compressed sensing methods, and reduces the size of the measurement matrix. It can use the same measurement matrix to measure signals of different sizes, meeting the diversity characteristics of medical data, and can also solve the problem of increased network energy consumption caused by the excessive storage and transmission of sensor data in WBAN. Therefore, for batch medical data with mixed signals, using STPCS technology to reduce the amount of data to be transmitted is a key step to realizing the high-efficiency and energy-saving forwarding model for WBAN.

Xie et al. [19] gave an authoritative mathematical model of STPCS as follows:

$$Y = \Lambda \propto X \tag{1}$$

in which $X \in R^z$, $Y \in R^{pz/q}$ and $\Lambda \in R^{p\times q}$ are sparse signal, observed value and semi-tensor measurement matrix based on perceptual data, respectively, and $\propto$ denotes a semi-tensor product. Because $z = lcm(q,z)$, Equation (1) can be converted to the following Equation (2):

$$Y = (\Lambda \otimes I_{z/q})X \tag{2}$$

where $\otimes$ represents tensor product, and Equation (2) can be expressed below:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{pz/q} \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1q} \\ \vdots & \ddots & \vdots \\ a_{p1} & \cdots & a_{pq} \end{bmatrix} \propto \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_z \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & 0 & & a_{1q} & \cdots & 0 \\ \vdots & \ddots & \vdots & \cdots & \vdots & \ddots & \vdots \\ 0 & \cdots & a_{11} & & 0 & \cdots & a_{1q} \\ & \vdots & & \ddots & & \vdots & \\ a_{p1} & \cdots & 0 & & a_{pq} & \cdots & 0 \\ \vdots & \ddots & \vdots & \cdots & \vdots & \ddots & \vdots \\ 0 & \cdots & a_{p1} & & 0 & \cdots & a_{pq} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_z \end{bmatrix} \tag{3}$$

In Equation (3), the row and column number of each small block of matrix Λ is z/p, and there are pq small blocks in total. The diagonal elements in the small block are a_{11}, a_{12}, ... , a_{pq} and the other elements are 0.

The reconstruction method of STPCS is parallel reconstruction method, and the semi-tensor measurement matrix satisfies the properties of cross-correlation, Spark condition and constrained isometry. Based on the STPCS, this paper proposes a STPCSE model, as shown in Figure 2.

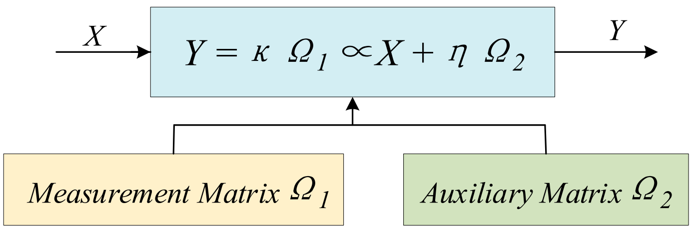


Figure 2. STPCSE model.

Obviously, in the evolution model $Y = \kappa\Omega_1 \propto X + \eta\Omega_2$ of STPCS, κ and η are variable parameters, Ω_1 is a $p \times q$ chaotic measurement matrix and the compression ratio is $CR = p/q$. The measurement matrix is generated by the Logistic chaotic system. The chaotic measurement matrix satisfies the constrained isometric property, which ensures the accurate reconstruction of compressed sensing. The auxiliary matrix Ω_2 is generated by the Tent chaotic system. The semi-tensor product breaks the dimension limitation of matrix multiplication and can realize matrix multiplication in the case of $q \neq z$, so that the measurement matrix can be used to encrypt signals with different dimensions. The measurement matrix, auxiliary matrix and parameters κ and η in the semi-tensor product contraction matrix evolution model can be flexibly adjusted to meet specific needs.

The STPCSE model still conforms to the general form of compressed sensing, and the derivation process is as follows:

$$Y = \kappa\Omega_1 \propto X + \eta\Omega_2 \Rightarrow \frac{Y - \eta\Omega_2}{\kappa} = \kappa\Omega_1 \propto X \Rightarrow \frac{Y - \eta\Omega_2}{\kappa} = (\Omega_1 \otimes I)X \tag{4}$$

In Equation (4), let $Y' = (Y - \eta\Omega_2)/\kappa$, $\Omega_1{}' = (\Omega_1 \otimes I)$, and then,

$$Y' = \Omega_1{}'X \tag{5}$$

According to the compressed sensing reconstruction algorithm, the signal X can be reconstructed based on Y' and $\Omega_1{}'$. Especially, when the parameters $\kappa = 1$ and $\eta = 0$, the model becomes a common STPCS $Y = \Omega_1 \propto X$.

In Equation (4), it is important to determine the values of Ω_1 and Ω_2, which solution process is as follows.

For Ω_1, firstly, the math equation of the Logistic system in the STPCSE model is shown in Equation (6):

$$x_{q+1} = \lambda x_q(1 - x_q), x_q \in (0, 1) \tag{6}$$

where λ ($\lambda \in [3.57, 4]$) is the control parameter, $x(q)$ is the generated Logistic chaotic sequence, x_q is the value of iteration q and x_{q+1} is the value of iteration $q + 1$.

The initial value of the Logistic system is 0.2 and the parameter is 4. When sampling the Logistic sequence, the initial sampling position is arbitrary. For the convenience of later calculation, the initial sampling value is set to 1. To reduce the correlation of the Logistic series, the sampling interval is set to 4 according to experience. Therefore, the sequence n can be obtained. According to the transformation $m = 1 - 2n$, the sequence m can be obtained. The measurement matrix Ω_1 can be obtained through column priority rearrangement for sequence m, which can be expressed as follows:

$$\Omega_1 = \sqrt{\frac{2}{p}} \begin{bmatrix} m_0 & \cdots & \cdots & m_{p(q-1)} \\ m_1 & \cdots & \cdots & m_{p(q-1)+1} \\ \vdots & \vdots & \vdots & \vdots \\ m_{p-1} & m_{2p-1} & \cdots & m_{pq-1} \end{bmatrix} \tag{7}$$

In Equation (7), the coefficient $\sqrt{2/p}$ is used for normalization.

Ω_2 is the auxiliary matrix of order $pz/q \times r$, which is generated by the Tent chaotic system. The mathematical formula of Tent system is shown in Equation (8).

$$\begin{cases} f_{q+1} = f_q/\mu, 0 < f_q < \mu \\ f_{q+1} = (1 - f_q)/(1 - \mu), \mu < f_q < 1 \end{cases} \tag{8}$$

in which μ ($\mu \in (0,1)$) is the control parameter, $f(q)$ is the generated Tent chaotic sequence and f_q and f_{q+1} are, respectively, the values of iterator q and iterator $q + 1$.

The parameter of the Tent system is 0.3, and the range of its initial value is (0, 1), and this paper sets the initial value of the Tent chaotic system as 0.23. Suppose that the generated Tent sequence is $f_1, f_2, \ldots, f_{q-1}, f_q, f_{q+1}, \ldots, f_{2q}$, the paper discards the first half $f_1, f_2, \ldots, f_{q-1}, f_q$ of the generated sequence and samples the second half $f_{q+1}, \ldots, f_{2q}$ of the sequence. The initial sampling position is 1, the sampling interval is 4, and the sampled sequence is $f_{q+1}, f_{q+5}, \ldots$, where q is half the length of the initial sequence. The auxiliary matrix Ω_2 is obtained by the column priority rearrangement of the sampling sequence.

3.2. Forwarding Model Based on Multi Factor Dynamic Fusion in TTCF

(1) Forwarding Decision Factors and Utility

Although reducing the amount of transmitted data can reduce the energy consumption of medical physiological data forwarding to a certain extent, the actual energy consumption of WBAN data forwarding is also affected by many other important factors such as residual energy of sensors, sampling frequency, and the nodal status in the network, which have essentially different effects on forwarding. The main reason is that most sensor nodes in WBAN have heterogeneous structures, and the energy consumption ratio of heterogeneous devices is different, so the contribution of each factor to sensor energy consumption and its relay capability is also different. For example, among the different types of medical data collected by WBAN sensors, vital data such as ECG and blood pressure must always be guaranteed, while information such as body temperature can be interrupted or delayed. That is, the importance of medical data collected by different sensors varies greatly, and the residual energy of sensors carrying important data must be kept at a high enough level to deal with emergencies. Thus, such nodes are not suitable to be used as relays; namely, they will not play a prominent role in WBAN data forwarding. Similarly, sensor nodes with higher sampling frequency usually consume more energy, so such nodes are not suitable for relay. That is, the sampling frequency of sensors is proportional to its energy consumption and inversely proportional to its forwarding capacity. Therefore, it is not accurate to directly use the above factors to evaluate the forwarding capability of relay nodes.

Moreover, as a special carrier of WBAN, the human body is always in the state of lying, sitting, standing, walking and different limb movements, which make WBAN maintain a dynamic environment. Meanwhile, due to the particularity of medical applications, some data acquisition can be completed soon, but there is still energy in these nodes, which can provide data forwarding services for other nodes. Thus, priority should be given to using their residual energy to make use of the residual energy of these nodes as early as possible, which can effectively improve the overall energy-saving effect of WBAN data forwarding and prolong its life. Therefore, considering the main factors affecting the energy consumption of medical sensors, combined with the different motion states of the human body, the research on the WBAN data forwarding model will be more in line with the needs of actual medical applications.

On the basis of Section 3.1 and on the premise of making full use of the nodes that will exit the network, this section takes the influence factors of sensor's sampling frequency, residual energy and its importance in the network as a decision-making value to measure the basic forwarding capacity of dynamic WBAN relay nodes, and selects the highest value as the best relay, so as to achieve the balance of the sensor energy consumption, extension of network life, and WBAN energy-saving transmission scheme with high forwarding efficiency.

Firstly, for the nodes that are about to exit the network, different characteristic flags are set for them to have a higher forwarding priority.

The process is as follows. Add the working time attribute t_j to node j. When t_j reaches the expected working time T_j, node j only forwards data. Therefore, when a node sends a status message, it judges the time parameter. If $t_j > T_j$, the residual energy influence factor value of node j is set to the maximum value 1, so that it can be selected as a relay node first.

Then, an appropriate mathematical model is constructed for each forwarding decision-making factor.

Assuming s_j is the sampling frequency of sensor j at a certain time, and because s_j is inversely proportional to the nodal forwarding capacity, this paper uses its reciprocal to define the importance factor of the nodal sampling frequency, as shown below.

$$\delta_j = \frac{1/s_j}{\sum_{j=1}^{N} 1/s_j} \tag{9}$$

The residual energy of sensors is proportional to their forwarding capacity. Supposing that the initial energy of sensor j is E_{ini} and the total energy consumed in each round of data collection is E_{cp}, the residual energy influence factor of sensor j is in the following:

$$\vartheta_j = \frac{E_{ini} - E_{cp}}{E_{ini}} \tag{10}$$

The importance of sensors in network data transmission can be expressed by the ratio of the number of packets forwarded by sensors to the number of packets forwarded by all the nodes in the network. Assume that sensor j has performed a total of τ_j forwarding operations before the current time, the importance factor η_j of sensor j in the network is shown as follows:

$$\eta_j = \frac{\tau_j}{\sum_{i=1}^{N} \tau_j} \tag{11}$$

Finally, the forwarding decision value of each encounter sensor in the network at the current time is calculated.

Leveraging the multi-factor dynamic decision method can effectively fuse nodal different attributes containing individual differences in their contributions to forwarding. This paper requires each relay node to provide a vector containing its multiple attributes in order to measure its forwarding ability. Suppose that sensor j is one of the relay nodes at some time, the forwarding capability metric FA_j of node j is as follows:

$$FA_j = \sum_{r=1}^{a} \omega_r A_r^j \tag{12}$$

In the paper, A_r^j denotes the attributes δ_j, ϑ_j and η_j of node j. The weight coefficient ω_r meets $1 \leq \omega_r \leq 0$ and $\sum_{r=1}^{a} \omega_r$=1, and means the different importance of each attribute. The EW method [28] is adopted to determine the weight of the attributes, and the information entropy of the r-th attribute is obtained according to Equation (13).

$$EW_r = -(\ln b)^{-1} \sum_{j=1}^{b} p_{rj} \ln p_{rj}, r = 1, 2, \cdots, a \tag{13}$$

In the equation, a represents the number of attributes of node j, b is the number of encounter nodes at this time and $p_{rj} = A_r^j \sum_{j=1}^{b} A_r^j$. Then, the weight coefficient of the r-th attribute of encounter nodes can be calculated according to the following equation.

$$\omega_r = \frac{1 - EW_r}{a - \sum\limits_{r=1}^{a} EW_r}, r = 1, 2, \cdots, a \tag{14}$$

Obviously, the weight value of an attribute of a node is inversely proportional to its information entropy EW_r, and the forwarding capability of a node is directly proportional to the value of its attributes. Namely, the smaller the information entropy of an attribute, the greater its weight should be; the larger the forwarding capability metric value, the stronger the forwarding ability of the encounter node, and the easier this node is to be selected as the relay node of the forwarding path.

In addition, in the short-range free space communication such as WBAN, the transmission power consumption is proportional to the transmission distance, which can be simply expressed as $E = \chi d^2$. In this equation, χ is a fixed parameter and its value in this paper is 0.0001, and d is the distance between nodes and can be calculated by using the European distance. Usually, when the distance between objects is doubled, energy consumption will be increased by four times. Thus, when relay nodes are added to a long-distance transmission, the energy consumption will be greatly reduced. While striving to improve the successful delivery rate of WBAN data, taking into account system energy saving, the paper will comprehensively consider energy consumption based on the distance between nodes and the nodal forwarding capacity measured by the importance factor of sampling frequency, the influence factor of residual energy and the importance factor of network status to build the forwarding decision utility.

Set ξ as the target node. If sensor i holds forwarding data at this time, when i transfers the data to ξ, i may be have a communication connection with multiple other sensor nodes (such as j) at this time due to the change of the network environment caused by the dynamic behavior of monitoring objects. Then, the selection condition of the next hop node, that is, the forwarding decision function, is as follows.

$$D_j = \alpha E_j + \frac{\beta}{FA_j} \tag{15}$$

where α and β are weight coefficients, which meet the requirements of $0 \leq \alpha, \beta \leq 1$ and $\alpha + \beta = 1$. The paper considers that it is equally important to measure the nodal energy consumption and forwarding capacity, namely, $\alpha = \beta = 0.5$. Obviously, the smaller the D_j value, the stronger the nodal forwarding capability and the lower the system energy consumption is.

(2) Forwarding Rule and Algorithm

WBAN is a wireless sensor network with a small number of nodes, and the star network topology is a simple topology, which is more suitable to be the first choice of WBAN network structure. However, in the star network topology, each node is independent of each other. When a node dies, there are still nodes with a large amount of residual energy, which leads to the excessive waste of network energy. Dijkstra algorithm can make good use of the relay function of the forwarding nodes to realize multi-hop transmission between remote nodes, greatly reduce network energy consumption and reasonably allocate network energy resources. It is very suitable for data transmission in WBAN. The idea of the original Dijkstra algorithm includes four steps. First, when calculating the shortest path in graph $G = (V,E)$ through Dijkstra, it is necessary to specify the starting node. Secondly, the node set V in G is divided into two sets V_i and $V - V_i$. V_i is to record the nodes that have been obtained in the shortest path and the corresponding shortest path length, while $V - V_i$ is to record the nodes that have not been obtained in the shortest path and the distance from the nodes to the starting node. Third, at the beginning, there is only the starting node i in V_i. In $V - V_i$, there are vertices other than i, and the path of vertexes in $V - V_i$ is "the path from the starting node i to these nodes". Then, find the node with the shortest path from $V - V_i$ and add it to V_i, and next, update the nodes in $V - V_i$ and the paths corresponding to the nodes. Fourth, repeat the above operation until all nodes are traversed.

Therefore, to prolong the lifetime of WBAN, the paper improves the Dijkstra algorithm in TTCF according to the actual needs, mainly changing the path parameters in Dijkstra into the comprehensive measurement of communication energy consumption between human sensor nodes and the forwarding ability of encounter nodes. The main pseudo codes executed by the improved Dijkstra algorithm at a certain time are as follows.

Obviously, Algorithm 1 can calculate the shortest path with the least energy consumption and the highest data transmission efficiency between the source and destination nodes according to the characteristics of the nodes and energy consumption between nodes. It can realize the reliable and lightweight forwarding of heterogeneous medical data by combining the STPCSE model, and the main pseudo code is shown in Algorithm 2.

Algorithm 1 Improved Dijkstra algorithm

Input: the starting node i with transmitted data, the target node ξ;
Output: forwarding path, namely, the node set containing all relay nodes j;
for each node j in G at time t *do*
  initialize the position coordinates of j;
  if $t_j > T_j$ *then*
    $\vartheta_j = 1$;
  else
    calculate ϑ_j based on **Equation (10)**;
  endif
  calculate δ_j and η_j of node j based on **Equations (9)** and **(11)**;
endfor
for $a = 0$ to $l - 1$ *do* //suppose it exists l nodes in the network at this time.
  for $b = 0$ to $l - 1$ *do*
    randomly generate communication relation matrix RE between nodes;
      //when $a{=}{=}b$, its value is set to 0 to avoid nodes forming a closed
      //loop, else 1.
    calculate the forwarding decision value between nodes based on the Euclidean distance between nodes and **Equations (12)–(15)**, and form a decision matrix D;
    endfor
endfor
use Dijkstra algorithm to find the shortest path $Road(i, \xi)$ between node i and ξ based on matrices RE and D; //$Road(i, \xi)$ is the transmission path with
  //the lowest energy consumption and the highest efficiency.
return $Road(i, \xi)$; // return in node traversal order between i and ξ.

Algorithm 2 TTCF algorithm

Input: the starting node i with transmitted data, the target node ξ;
Output: the flag *flag* indicating whether the packet is successfully forwarded;
flag = 0;
while i != ξ *do*
  for any packet Pk to be transmitted on node i at time t *do*
    compress Pk based on **STPCSE** model;
    use **Algorithm 1** to gain $Road(i, \xi)$;
    if $Road(i, \xi)$!= Null *then*
      node i transmits Pk to node ξ;
      flag = 1;
      delete Pk from the queue of node i;
    else
      node i continues to hold Pk, waiting for the calculation, judgment and transmission of the next time, or if Pk expires, node i directly deletes Pk and terminates this cycle;
    endif
    return flag;
  endfor
endwhile

It can be seen from the above, the nodes carrying the forwarded data in WBAN can complete the lightweight data transmission from the source node to the sink node by calling Algorithm 2.

4. Experiments Analysis and Discussion

4.1. Experimental Environment and Parameters Setting

In WBAN, multi-hop data transmission can effectively reduce system energy consumption and prolong network life. This paper adopts a simulation experiment to verify the feasibility and efficiency of the proposed TTCF strategy; the experimental platform uses MATLAB 2020B, and the computer is mainly configured as a CPU 2.39 GHZ, 8 GB Memory, 64 bit Windows 10 operating system. In WBAN, the sensors with different health monitoring functions are distributed in the head, feet, legs, thighs, knees, abdomen, back, waist, chest, upper arm, forearm, neck and other parts of the human body, and are responsible for collecting physical signals such as blood pressure, blood oxygen, temperature, ECG, EEG, EMG and electroretinogram. With the change of human behavior, such as lying, sitting, standing and walking, or the loss of sensor energy, the relative position of the sensors on each part also changes. Obviously, the WBAN network environment is changing all the time. Due to the different functions of each sensor, their data rate, corresponding sampling frequency and initial energy are also greatly different. For example, the ECG and EEG sensors should have higher sampling frequency and initial energy than the temperature and blood pressure sensors, because the latter only reflects whether a person is healthy, while the former is a key signal that can reflect whether a person is alive or not. Therefore, in this paper, various functional sensors are set with different data rates, sampling frequencies and initial energy, as shown in Table 1.

Table 1. Sensor type and related parameters.

Sensor Type	Data Rate (Kbps)	Sampling Frequency (HZ)	Initial Energy (J)
temperature	2.4	0.1	50
blood pressure	1.44	60	50
blood oxygen	7.2	300	80
EMG	45	150	60
EEG	60	200	70
ECG	72	250	70

For ease of calculation, the energy consumption of all sensor nodes when compressing data is 0.05 J/bit, the energy consumption when transmitting data is set to 1 J/kb, the number of packets collected on each node is 10 to 100 and the size of each data packet is 1 KB to 2 MB. It is assumed that there is one sink node and 15 sensor nodes in WBAN at a certain time. The specific distribution is shown in Figure 3.

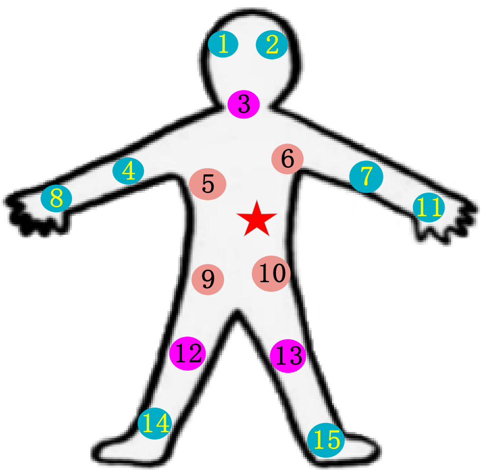


Figure 3. An example scenario of node distribution in WBAN.

In Figure 3, the red five-star represents the sink node, the position of which is the coordinate origin, and the positions of the other nodes are assigned with the sink node as the origin according to the posture of the human body at a certain time. The sensor node type is allocated according to its human body position, and it is necessary to ensure that there is at least one type in Table 1. Based on the node positions shown in Figure 3, EEG nodes include 1 and 2, ECG nodes are 5, 14 and 15, EMG nodes have 10, 12 and 13, blood pressure nodes contain 4 and 7, blood oxygen nodes are 3, 6 and 9 and temperature nodes include 8 and 11. According to the node distribution in Figure 3, sensors 5, 6, 9 and 10 are the four closest to the sink node and usually undertake a large number of forwarding tasks; 3, 12 and 13 are sensors close to the sink node, which usually undertake some forwarding tasks; and the other nodes are the nodes farthest from the sink node, and usually rarely participate in task forwarding.

TTCF first uses the STPCSE model to minimize the amount of physical data on the WBAN sensors, and then transmits the compressed data to the human body sink node. Generally, human sensors far away from the sink node have to use relay nodes for data transmission, so multiple transmission paths composed of different nodes may be formed between the source nodes and sink nodes. The purpose of TTCF is to select the optimal path nodes from these paths for data transmission and convergence.

4.2. Comparison Model and Metrics

To verify the reliability and energy saving of our proposed TTCF strategy, this paper will use UC-MPRP [29] and CRPBA [30] to compare and analyze it. UC-MPRP leverages a node-independent multi-path routing model to design a multi-path route between clusters, and CRPBA is a one-hop forwarding model. The two models did not consider data compression before transmission; thus, this paper firstly computes data reconstruction error to judge the performance of compressing data for our TTCF. According to the definition of the reliability in [56] and the purpose of green computing, this paper will adopt a cumulative delivery rate, residual energy and throughput to measure the reliability and energy saving of all the above models. The metrics are defined as follows.

- Data Reconstruction Error

The measurement matrix Ω_1 is a $p \times q$ -order matrix generated by the Logistic chaotic system of Equation (7), and the sparsity is set to δ. The auxiliary matrix Ω_2 is a matrix generated by the Tent chaotic system of Equation (10). To ensure the uniqueness of sparse recovery, the maximum value of sparsity δ is $p/2$. The process of constructing a one-dimensional signal in the experiment is as follows:

$$\begin{aligned} init &= randperm(q) \\ x &= zeros(q,1) \\ x(init(1:\delta)) &= randn(\delta,1) \end{aligned} \tag{16}$$

where x is a one-dimensional signal, q is the signal length. In this paper, the signal length is set to 240, that is, $x \in R^{240}$, the maximum sparsity is set to 60, and the positions of non-zero elements are randomly generated. If x is the original signal and the reconstructed signal is x', the reconstruction error is calculated as shown in Equation (17).

$$\frac{\|x - x'\|}{\|x\|} \tag{17}$$

This paper considers that the reconstruction is successful when the reconstruction error of the experiment is less than 10^{-6}.

- Cumulative Delivery Rate

$$C_{dr} = \frac{PK_{received}}{PK_{sent}} \tag{18}$$

where $PK_{received}$ represents the number of packets successfully received by sink node, and PK_{sent} is the number of packets sent by all the human body sensor nodes.

- Residual Energy

It includes data compression energy consumption and transmission energy consumption. Assuming that Q-dimension transmission data on the i-th sensor is compressed into the P- dimension by using the STPCS evolution model, the data compression energy consumption per unit time on sensor i is as follows:

$$E_{stp} = \left(2Q \times \sqrt{PQ} + PQ\right) \times E_{sc} \tag{19}$$

where E_{sc} denotes the energy consumed to compress one bit of data, and its value is 0.05 J/bit.

The energy consumption of data transmission per unit time is shown in Equation (20).

$$E_{tr} = J_e \times d_{v-i} \times t_{tr-i} \tag{20}$$

where J_e represents the energy consumption of data transmitted by sensors, and its value is 1 J/KB; $d_{v\text{-}I}$ and $t_{tr\text{-}i}$, respectively, representing the data rate (shown in Nomenclature part) and the transmission duration of the i-th relay sensor on the transmission path, so the calculation method of sensor energy consumption is shown in Formula (21).

$$E_{total} = E_{stp} + E_{tr} \tag{21}$$

Obviously, sensor residual energy is the difference between its original energy and energy consumption E_{total}, and the residual energy of the networking is the sum of the residual energy of all sensors.

- Throughput

$$Tr = \frac{1}{T_{received} - T_{sent}} \sum_{\kappa=1}^{K} R_{bytes}(\kappa) \tag{22}$$

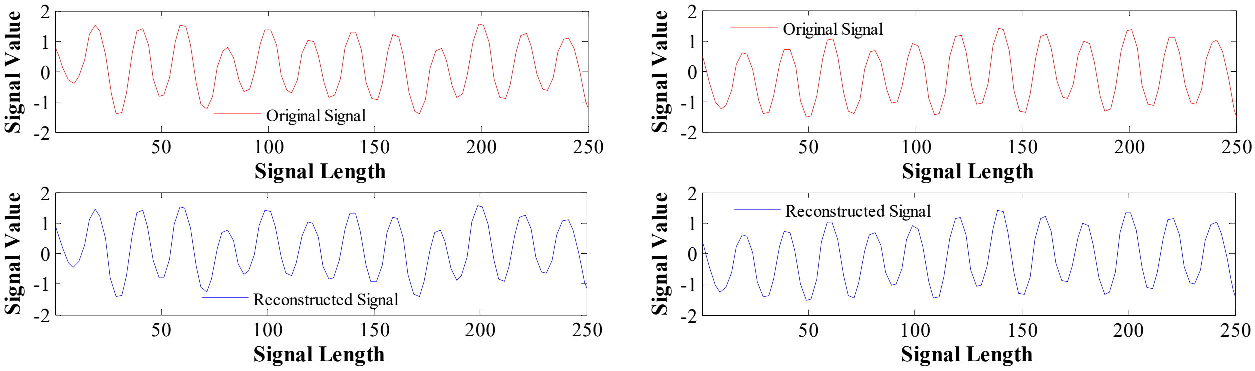
where K is the number of packets transmitted to the sink node successfully on sensor i, $R_{bytes}(\kappa)$ represents the number of bytes when the κ-th packet successfully reaches sink node, $T_{received}$ represents the time when the sink node starts receiving packets on sensor i and T_{sent} denotes the time when the sink node ends receiving packets on sensor i.

Network throughput refers to the total amount of data successfully transmitted to the sink node. Thus, the networking throughput is the sum of the throughput of all sensors. The higher the throughput, the more stable the network and the better the performance is.

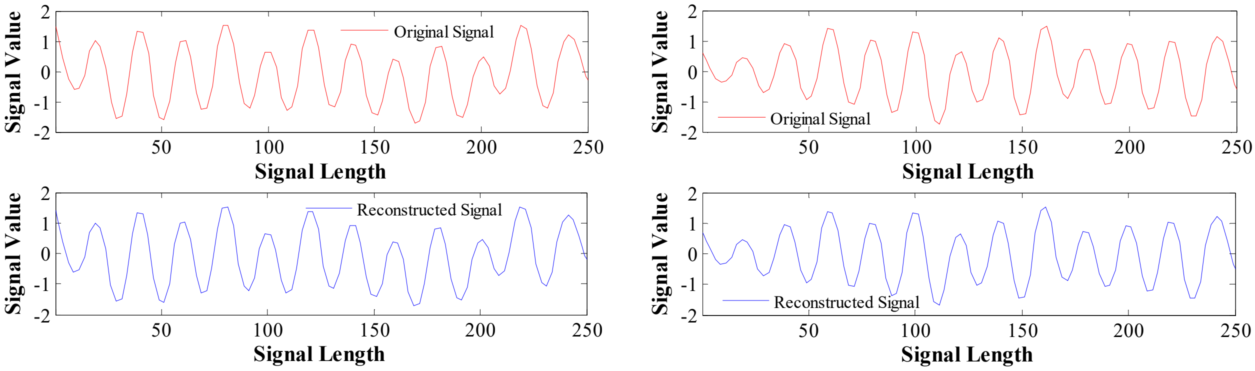
4.3. Performance Evaluation and Analysis

This paper measures the adaptability and effectiveness of the TTCF mechanism based on the STPCSE model by evaluating the performance of data reconstruction accuracy, cumulative transmission delay, energy consumption and throughput under various conditions.

Figure 4 describes the relationship between the signal length and signal value when the measurement matrix and auxiliary matrix are changed, respectively. The abscissa and ordinate are the signal length and signal value, respectively. Figure 4 shows two sets of data of the original signal and reconstructed signal. The sparsity is 20, that is, there are 20 non-zero elements in the 240-length signal. In Figure 4a, the auxiliary matrix is kept as the Tent chaotic matrix, and the measurement matrix adopts the Gauss matrix and Logistic chaotic matrix, respectively. According to Equation (17), their reconstruction errors are, respectively, 1.19×10^{-14} and 1.1019×10^{-15}. Since it is specified in advance that the reconstruction is successful if the reconstruction error is less than 10^{-6}, obviously, for these two different measurement matrices, the original signal can be reconstructed correctly, and the reconstruction error is very small. Figure 4b shows the changed relationship between the reconstructed signal and the original signal when the measurement matrix is the Logistic chaotic matrix and the auxiliary matrix is the Gaussian matrix and Logistic chaotic matrix, respectively. Obviously, in this case, the difference between the reconstructed signal and the original signal is also very small. Their reconstruction errors are, respectively, 1.1719×10^{-15} and 1.5119×10^{-15} based on Equation (17), which are significantly smaller than the predetermined reconstruction errors, and the signal can be reconstructed successfully. Seen from the above, the STPCSE model in TTCF can effectively compress the physiological index data collected by the WBAN sensors.



(**a**)



(**b**)

Figure 4. (**a**) Influence on signal reconstruction when the measurement matrix is Gaussian matrix and Logistic chaotic matrix, respectively; (**b**) Influence on signal reconstruction when the auxiliary matrix is Gaussian matrix and Logistic chaotic matrix, respectively.

Figure 5 reflects the relationship between the cumulative delivery rate of data and the lifetime of packets (TTL, Time to Live) with and without the TTCF scheme. Due to the limitation of the buffer size or capacity of sensor nodes in WBAN, with the increase of TTL, the cumulative delivery rate in both cases increases first and then decreases. Moreover, the cumulative delivery rate of the algorithm without TTCF is significantly lower than that of the algorithm with TTCF. The main reason is that the latter makes use of the characteristics of the nodes to measure their forwarding capacity more scientifically and reasonably, and makes an objective evaluation of the transmission energy consumption between the nodes by using the Euclidean distance, and then combines the two to improve the path calculation method in the Dijkstra algorithm, so as to speed up the selection of the relay node sequence of the optimal path between the source-destination nodes in the data forwarding process. Thus, the time of data transmission is shortened, and the delivery rate of data is improved, which is more applicable.

The reliability of the model can be verified by the size of the network cumulative delivery rate. The cumulative delivery rate of the following three time points is randomly selected, as shown in Figure 6. It can be seen that our TTCF is superior to the other two, that is to say, the reliability of the TTCF is the highest. The main cause is that CRPBA forwards data directly within and between clusters in a one-hop manner, which is easy to cause forwarding failure and has a low packet delivery rate. Although UC-MPRP uses a multi-path routing mechanism to improve the delivery success rate of data, it does not take into account the heterogeneity of data and the difference of nodes' status in the network, and multi-path routing will cause some nodes to be occupied for a long time so that they cannot participate in other forwarding services, which directly leads to the decline of the overall delivery rate of the network. Therefore, the TTCF protocol proposed in this paper shows a good performance in terms of data delivery rate or reliable data transmission.

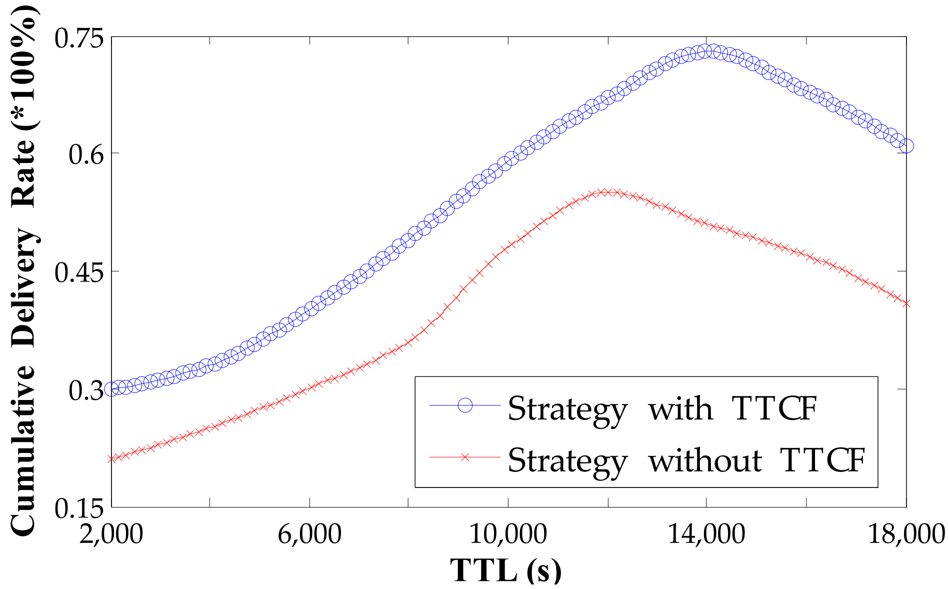


Figure 5. Comparison of cumulative delivery rate of data forwarding model with and without TTCF strategy.

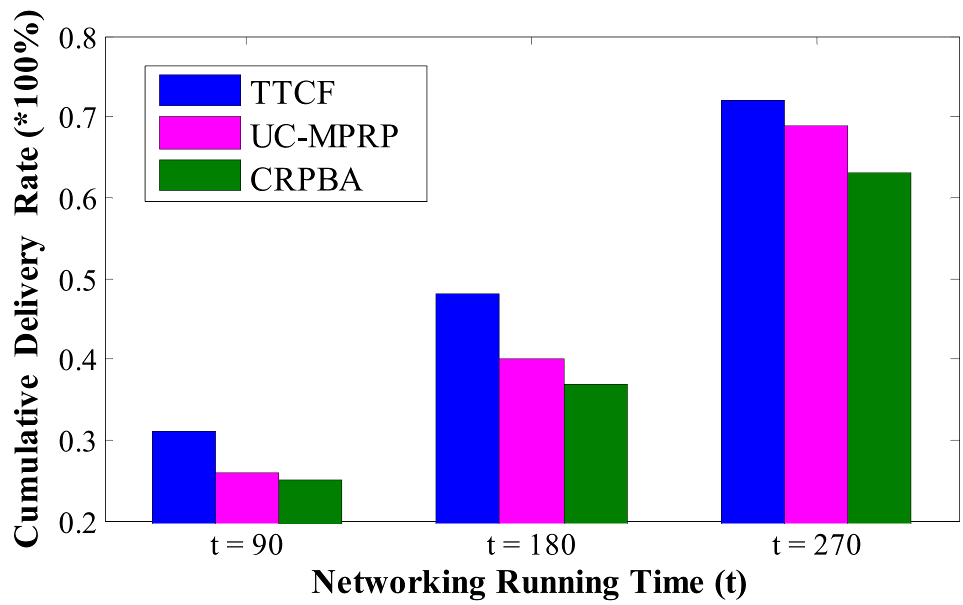


Figure 6. Comparison of cumulative delivery rate of TTCF, UC-MPRP and CRPBA at different times.

Figure 7 shows the trend of the residual energy of various sensor nodes distributed in different positions of the human body as the number of data sending rounds changes. Obviously, the remaining energy of all the sensor nodes continues to decrease with the increase of sending rounds. Moreover, the four nodes closest to the sink node consume the fastest energy, followed by the three nodes with the number of 3, 12 and 13, which are slightly farther away. The main reason is that these sensors near the sink node not only undertake the task of sending their own data information, but also undertake the forwarding task of most other nodes in the WBAN. The nodes farthest from the sink consume the slowest energy and change relatively smoothly, but some of the farthest nodes (such as the nodes numbered 4, 7, 8, 11) have less residual energy than the nodes that are slightly closer. This is because the nodes numbered 4, 7, 8 and 11 are located on the arms on both sides of the human body, and the arm swing or embrace and other actions make them sometimes closer to the sink node than the nodes numbered 3, 12 and 13, and there are also more opportunities to participate in transmission calculation as a relay. However, there is an inflection point in the residual energy of the sensors slightly away from the sink node, which is because after the sensor nearest to the sink node dies, these nodes farther away from the sink node need to undertake the task of sending data directly to the sink node. The residual energy inflection point of the sensors farthest from the sink node appear the latest, because almost all the nodes that are closer to the sink node die at this inflection point, and then the sensor nodes farthest from the sink node depletes their energy and begin to die. The TTCF dynamically adjusts whether a node participates in data forwarding according to its status (whether it has completed the task and is about to quit the network) and the actual situation of its remaining energy value, so as to make the network energy consumption as balanced as possible, extend the network life and improve the data transmission rate. The approximate same curve trend in Figure 7 verifies the correctness of this conclusion.

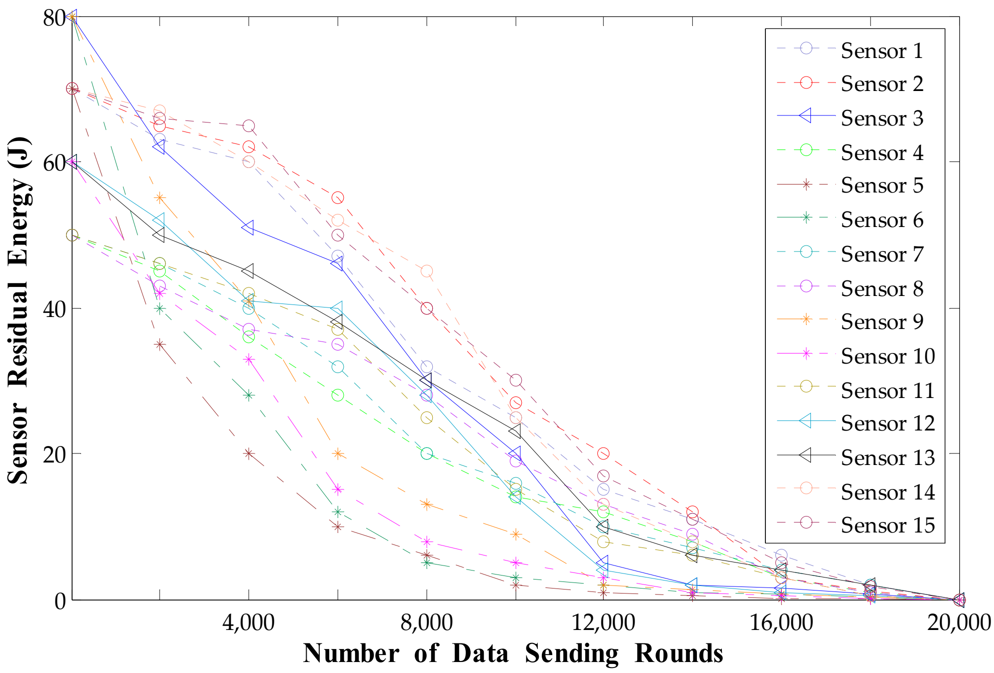


Figure 7. Comparison of residual energy of each sensor node after applying TTCF strategy.

To analyze the performance of the TTCF strategy in terms of energy utilization efficiency, it is necessary to detect the energy utilization of the nodes in each round. Figure 8 shows the comparison of the residual energy between TTCF and UC-MPRP and CRPBA. Obviously, the energy-saving effect of TTCF is better than that of UC-MPRP and CRPBA. When designing transmission paths within and between clusters, CRPBA directly forwards data in a one-hop manner, which will cause data forwarding failure and consume more energy. The minimum energy threshold set by UC-MPRP is for all nodes. In practical applications, different energy thresholds need to be set according to different node locations and different forwarding tasks, so as to balance the network energy consumption. Therefore, UC-MPRP has unbalanced energy consumption and an unstable system, which will consume more energy in order to maintain the normal operation of the system. Compared with the above two, TTCF uses compression sensing technology to effectively compress the data volume, which can greatly reduce the network transmission volume. Moreover, the improved Dijkstra algorithm based on the effective multi-attribute decision value reduces the time to find the reliable path between the source and target nodes, and consumes less network energy while improving the transmission efficiency.

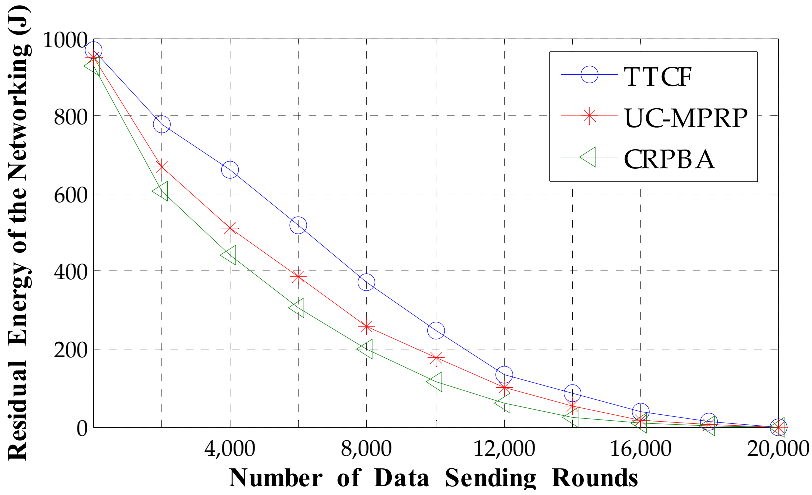


Figure 8. Comparison of residual energy of the networking between TTCF, UC-MPRP and CRPBA.

Figure 9 exhibits the throughput change of each sensor node after using the TTCF strategy. Seen from Figure 9, although the sensors closest to the sink node have the shortest life cycle, its throughput is the largest, indicating that it undertakes a large number of forwarding tasks. The difference in the lifetime and throughput of the sensors farthest from sink node is not obvious, which indicates that these sensors do not undertake any forwarding tasks, while the throughput of the sensors between the above two types of nodes reflects that they undertake some forwarding tasks.

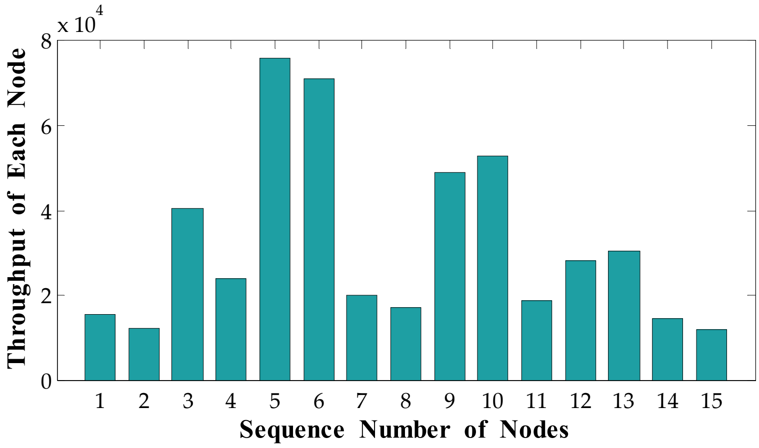


Figure 9. Throughput performance of each sensor node after applying TTCF strategy.

Figure 10 describes the comparison of the networking throughput between this TTCF strategy and CRPBA and UC-MPRP. Seen from it, the line trend of TTCF is higher than that of CRPBA and UC-MPRP. CRPBA uniformly clusters the nodes in the network without considering the difference of the forwarding capabilities between the network center and the network edge nodes, resulting in the low utilization of some capable nodes, low data processing efficiency and poor network throughput. UC-MPRP adopts the multi-path routing transmission method, which enables more nodes in the network to participate in the data forwarding task and improve the forwarding efficiency. However, because some important nodes participate in multiple routing calculations and queuing waiting, it is very easy to cause network congestion and a low system throughput under the flow of big data. The higher throughput achieved by TTCF is because data compression makes the network capacity increase, and the forwarding mechanism based on multiple important attributes of nodes makes the number of data packets successfully delivered to the sink nodes increase greatly, the network processing ability enhance, and the networking throughput improve.

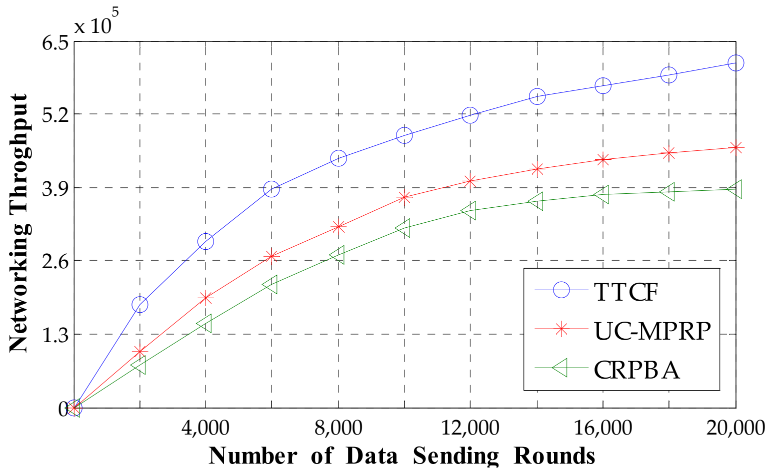


Figure 10. Comparison of networking throughput between TTCF, UC-MPRP and CRPBA.

5. Discussion

The proposed TTCF model combines two measures to make full use of the surplus energy of the sensor nodes to improve the efficiency and reliability of WBAN while transmitting data. One is to compress data by using the proposed STPCSE model, which can effectively reduce the amount of data to be transmitted and reconstruct the original signal with high accuracy. The other is to develop a new forwarding strategy that comprehensively considers multiple attribute factors of nodes, and it can measure the forwarding capacity of relay nodes and system energy consumption and raise the performance of forwarding algorithm. A large of experimental results prove that the proposed TTCF strategy is superior to the comparison scheme in many aspects.

Although the TTCF strategy improves the reliability of WBAN data forwarding to some extent, there are still some deficiencies. Firstly, WBAN relies on mixed wireless channels that mainly include a free space channel, body surface channel and body internal channel. This paper does not reflect on the differences of communication models under these three paths for the convenience of calculation, which will affect the accurate calculation of energy consumption. Secondly, this paper believes that node energy consumption and forwarding capacity are equally important, which may lead to the loss of objectivity in selecting relay nodes in forwarding path calculation. Therefore, we plan to solve the above two defects in the next step. First, to give the transmission power consumption closer to the real environment, we will replace the calculation method of power consumption based on the Friis model [57] with various losses L greater than 1, which can measure the actual power consumption in a non-ideal communication state more accurately, and can also well reflect the WBAN data transmission environment with mixed communication channels. Then, we consider using the adaptive weight approach [58] to fuse the related items in the Equation (15). The weight given by this adaptive weight method is not fixed and inconvenient. It is adjusted according to the useful information in the current solution set, thus forcing the algorithm to search in the direction of the Pareto frontier. Compared with the fixed weight assigned by the human, it has greater advantages and adaptability. These improved plans will be reflected in the contents of our further research.

6. Conclusions

In WBAN applications, the energy of sensors is limited and difficult to supplement, so it is very necessary to reduce the energy consumption of sensors as much as possible for achieving smooth transmission of WBAN data and the sustainability of service. Compress sensing data by eliminating redundancy can effectively reduce the amount of data transmission and improve the system operation efficiency. Thus, the paper first considers the accuracy of reconstructed signals and uses the proposed STPCSE model to implement it, which not only reduces the amount of data transmission, but also encrypts the data to a certain extent through compression and decompression rules. This is the most basic processing measure to ensure lightweight and safe data transmission. Secondly, the performance improvement of the data forwarding mechanism is also a key means to ensuring high and reliable data transmission. This paper improves the WBAN data forwarding mechanism based on social relations by integrating multiple attribute factors, high-performance methods or algorithms, such as the influence factors of the sampling frequency, residual energy and nodal importance, European distance, EW method and Dijkstra optimization algorithm. Then, the TTCF strategy based on human limb dynamic behavior is proposed. It fuses the STPCSE model and the improved data forwarding mechanism, and leverages the latter to pass the compressed data based on the former, and realize the lightweight, safe, reliable and effective data transmission for WBAN. Finally, a large number of simulation experiments and performance comparison analysis results show that TTCF has good performance in data reconstruction error, cumulative delivery rate, energy-saving effect and throughput. For example, its cumulative delivery rate is about 12% and 20.8% higher than that of UC-MPRP and CRPBA, and its residual energy and throughput are 1.22 times and 1.41 times, 1.35 times and 1.6 times of the latter two, respectively.

Author Contributions: Conceptualization and methodology, J.L. and J.Y.; writing, J.L.; supervision, J.Y.; data curation and validation, J.L. and J.X.; investigation and visualization, J.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (grant number 62002028, J. Y.).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank the editors and anonymous reviewers for their insightful suggestions to improve the quality of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

WBAN	Wireless Body Area Network
TTCF	Two-Tier Cooperation based high-reliable and lightweight Forwarding
STPCS	Semi-Tensor Product Compress Sensing
ECG	Electrocardiograms
EEG	Electroencephalograms
EMG	Electromyography
QoS	Quality of Service

Nomenclature

Symbol	**Meaning**
X	sparse signal
Y	observed value
Λ	Semi-tensor measurement matrix
$\propto$	Semi-tensor product
$\otimes$	tensor product
Ω_1	chaotic measurement matrix
Ω_2	auxiliary matrix
i, j, ε	sensor node
t_j	the working time attribute of node j

δ_j	the sampling frequency of node j
ϑ_j	the residual energy influence factor of node j
η_j	the important factor of node j
ω_r	the weight coefficient of the r-th attribute
E_j	energy consumption between node with data and node j
D_j	the utility measuring the forwarding capability of node j
C_{dr}	data delivery rate
E	sensor residual energy
T_r	sensor throughput

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