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**BGMM: A Body Gauss-Markov Based Mobility Model for Body Area Networks**

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Yi Liu, Danpu Liu*, and Guangxin Yue

Abstract: Existing mobility models have limitations in their ability to simulate the movement of Wireless Body Area Network (WBAN) since body nodes do not exactly follow either classic mobility models or human contact distributions. In this paper, we propose a new mobility model called Body Gauss–Markov Mobility (BGMM) model, which is oriented specially to WBAN. First, we present the random Gauss-Markov mobility model as the most suitable theoretical basis for developing our new model, as its movement pattern can reveal real human body movements. Next, we examine the transfer of human movement states and derive a simplified mathematical Human Mobility Model (HMM). We then construct the BGMM model by combining the RGMM and HMM models. Finally, we simulate the traces of the new mobility model. We use four direct metrics in our proposed mobility model to evaluate its performance. The simulation results show that the proposed BGMM model performs with respect to the direct mobility metrics and can effectively represent a general WBAN-nodes movement pattern.

Key words: mobility metric; mobility model; human movement model; random Gauss-Markov; Wireless Body Area Network (WBAN)

1 Introduction

1.1 Wireless Body Area Network (WBAN)

The WBAN, also referred to as the wireless body sensor network, is a wireless network of wearable devices arranged around the human body. The sensors in a WBAN may be embedded or implanted inside the human body, or may be affixed to the surface of the body in a certain position. These sensors can detect and collect physiological data such as blood pressure, heart rate or body temperature, as well as environmental data such as air temperature, humidity, or wind[1–5].

The most prominent feature of WBANs is that their network sensors use the human body or clothing as network carriers. Since the WBAN sensors are embedded or affixed to the human body, the WBAN moves with the body. A WBAN can also be regarded as a mobile sensor network with a small number of nodes. Usually, the number of WBAN nodes ranges from three to 50. In different mobile network applications, nodes have different mobility patterns, and these patterns have a great impact on network topologies. Mobility models describe the movement pattern of nodes in mobile networks and provide an important basis for mobile network simulation. Analysis of mobile network performance is critical in network simulation, as it can guide the design and improvement of network protocols. Even if the number of nodes in WBAN is not large, the data merits attention. In medical monitoring, the data in a WBAN is strongly related to the human’s health condition. A one-hop
route cannot ensure reliable transmission. Many routing algorithms are used to guarantee reliable data transmission in a WBAN. Therefore, the construction of a WBAN mobility model is a significant step toward the design of a WBAN route algorithm and the analysis of WBAN performance\[4, 6–9\].

1.2 Current WBAN mobility model

Existing mobility models are mostly oriented to Ad hoc networks or wireless sensor networks. These models have significant limitations in their ability to identify human body movement and only very little research has been conducted on WBAN mobility models.

In Ref. [10], the research group proposed a node mobility model oriented to WBANs, but the author does not provide a mathematical model for simulation or evaluation.

In Ref. [11], the author developed a Small-World-In-Motion (SWIM) mobility model for WBAN, but this type of models does not take body node groups into consideration.

In Ref. [12], the authors proposed a new mobility model for the movement of nodes affixed to the human body based on different postures such as standing, sitting, and laying down. Although this model can identify different bodily postures, it cannot represent the state of transformation between different postures.

WBANs depend on the sensors embedded on or implanted into human body. A WBAN mobility model should not only satisfy the mobile network requirements, but also reflect the characteristics of human body movement. On this basis, we take human body movement into consideration, in our proposed Body Gauss–Markov Mobility (BGMM) model\[13, 14\].

1.3 BGMM overview

In this study, we propose a new WBAN mobility model we call the BGMM. First, by comparing and analyzing typical existing mobility models, we regard the Random Gauss-Markov Mobility (RGMM) model as the most suitable basic framework for developing a WBAN mobility model. Secondly, we construct a new simplified Human Mobility Model (HMM), since the RGMM model is a single-node model. The new simplified HMM extends the single node of the RGMM to a group of nodes. Then we further develop this new RGMM model by combining an Ad hoc network mobility model with the simplified HMM model and then evaluate its effectiveness using four metrics.

2 Existing Mobile Network Mobility Models

To date, many researchers have developed Ad hoc network mobility models, with more than 40 mobility models in Ad hoc networks reported[11]. It is worthwhile investigating Ad hoc network mobility model, since there are many similarities between Ad hoc networks and WBANs. Both are self-organization networks, and each of their nodes can communicate with other nodes directly or by a limited number of hops. However there are also many differences between Ad hoc networks and WBANs. First, WBANs are usually battery-powered, whereas Ad hoc networks have a steady power supply. Second, WBANs have a sink node, also referred to as a coordinator, whereas the Ad hoc does not. Third, each individual node movement in a WBAN follows a principle of human body movement whereas each node in an Ad hoc network moves randomly or follows other principles. As such, we cannot directly apply Ad hoc network mobility models to WBAN model directly, but we can use Ad hoc network mobility models as a reference in the development of a WBAN mobility model[15–17].

2.1 Classification of Ad hoc network mobility models

Mobility models use datasets or mathematical equations to describe the movements of nodes, based on node location, movement speed, and direction. Usually, Ad hoc network mobility models have two classifications: entity and group mobility models. Entity mobility models describe the movement of a single node or several independent nodes and group mobility models describe the movement of a group of relative nodes[11, 18, 19].

2.2 Analysis on commonly used Ad hoc network mobility model

As noted above, at least 40 Ad hoc network mobility models have been reported in the literature[11]. In our previous work on mobility models[20], we investigated some commonly used Ad hoc network mobility models. Based on the features of WBANs, which we discuss in Section 3.2, and given the node topology, a WBAN can be regarded as either a group or an entity. When the human body moves, the associated nodes will move as a group, and the nodes in a WBAN can be regarded as a group. On the other hand, if we consider the human body mobility model, a single node in an entity mobility model can be extended to group nodes. In this respect, entity and group mobility models both provide a suitable basis from which researchers can develop a WBAN mobility model.

An effective mobility model should meet the following
criteria\cite{21}:

(1) Ability to identify the actual human scenario.

(2) The model parameters can be adjusted to adapt to different scenarios.

(3) Simplicity and efficiency.

Regarding the characteristics of human movement, we chose models with performances most similar to that of a WBAN for comparison. The Random Walk Mobility (RWM) model is the most similar and satisfies the simplicity requirement of a WBAN mobility model. The Random Way Point Mobility (RWPM) model also takes into account the pause factor, which is similar to actual human movement. In the RGMM model, the node movement in each step is not random and is correlated with its past and current locations and velocities, which is much more similar to actual human movement but also more complex than the RWPM model. The Nomadic Community Mobility (NCM) model is a group mobility model, which accords with the multiple nodes in a WBAN\cite{20}.

Therefore, we chose four models for our analysis and comparison, which are listed in Table 1.

As demonstrated in Ref. \cite{22}, the RWM model has the lowest average end-to-end delay and average hop count.

<table>
<thead>
<tr>
<th>Table 1 Comparison of Ad hoc mobility modules.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>Random Walk Mobility (RWM)</td>
</tr>
<tr>
<td>Random Waypoint Mobility (RWPM)</td>
</tr>
<tr>
<td>Random Gauss-Markov Mobility (RGMM)</td>
</tr>
<tr>
<td>Nomadic Community Mobility (NCM)</td>
</tr>
</tbody>
</table>

The RWPM model has the highest data-packet delivery ratio and average link duration, which means it is simple and much more efficient than the other three. The traveling pattern of the RGMM model is mostly similar to human body movement, and the memory level parameter can be adjusted to adopt different scenarios. The NCM model has a higher average relative speed than the other three\cite{22, 6, 21}.

Based on these conclusions, we find that the RGMM model meets the first and second criteria, so we used it as the theoretical basis for this study. However, the RGMM model is an entity mobility model and there are many nodes in WBANs. As such, we must transform the RGMM into a group mobility model by combining it with an HMM. In Section 3, we describe the construction of an HMM.

2.3 RGMM model

The RGMM model is based on the Gauss–Markov process, which is widely used in many fields, including signal estimation and economic forecasting. By adjusting the parameters, the RGMM model can establish a correlation between the velocities of mobile nodes in time, based on the fact that a node changes its movement speed and direction at fixed intervals of time $n$. The speed and direction at the $n$-th instance is determined by the speed and direction at the $(n-1)$-th instance. The velocity is expressed in Eq. (1).

$$v_n = \alpha v_{n-1} + (1 - \alpha) \mu + \sigma(\sqrt{1 - \alpha^2}) w_{n-1} \tag{1}$$

where $\alpha$ is the memory level, $0 < \alpha < 1$; $\mu$ is the mean of velocity; $\sigma$ is the standard deviation; $w_n$ is the uncorrelated Gaussian process at time $n$.

The speed $|v_n|$ and the direction angle $\theta_n$ of the velocity are expressed as shown in Eqs. (2) and (3), respectively:

$$|v_n| = \alpha |v_{n-1}| + (1 - \alpha) \mu_r + \sigma_r(\sqrt{1 - \alpha^2}) w_{n-1} \tag{2}$$

$$\theta_n = \alpha \theta_{n-1} + (1 - \alpha) \mu_\theta + \sigma_\theta(\sqrt{1 - \alpha^2}) w_{\theta n-1} \tag{3}$$

where $\{w_{v n-1}\}$ is an uncorrelated Gaussian process with a zero mean and unit variance and is independent of $\{v_{n-1}\}$; $\{w_{\theta n-1}\}$ is an uncorrelated Gaussian processes with zero mean and unit variance and is independent of $\{\theta_{n-1}\}$. The coordinate of the node is given in Eq. (4) and Eq. (5), respectively.

$$x_n = x_{n-1} + |v_{n-1}| \cos\theta_{n-1} \tag{4}$$

$$y_n = y_{n-1} + |v_{n-1}| \sin\theta_{n-1} \tag{5}$$
3 Construction of Human Mobility Model

In this section, we present a simplified human body movement topology and mathematical human body movement model.

3.1 Current HMMs

As noted above, the nodes in a WBAN should follow human body movement, so the HMM is also an essential aspect of the WBAN mobility model. Research on human mobility has attracted the interest of many researchers who have varying levels of interest in HMM simulation. HMMs are widely applied in games, animation, film and television special effects, and biomechanics, to name a few\cite{23, 24}.

In their biomechanics paper, the authors in Ref. [25] determined the basic relationships between biophysics data and human mobility. Robot manufacture researchers combine a physics controller with real human mobility, and researchers in computer science create a virtual reality environment based on huge amounts of scanned data.

Although many researchers have developed models of human body movement, these models have mainly focused on the mechanics, 3D reconstruction, or data point cloud. Although some models of human body movement have incorporated topology or node position, these models are too complex to directly apply in WBANs. Because some models consider the impact of muscles, they must collect huge volumes of data to reconstruct the human body.

The human body is a very complicated system. Since the movement of human beings is controlled by their own will and is subject to great random probability, it is difficult to accurately describe human body movement based on a mathematical model. It is also difficult to confirm the validity of an HMM simulation. A WBAN need not use its sensors to consider the impact of muscles and it is also difficult for a WBAN to process so much data. If the above models were directly applied in a WBAN, they would not satisfy the simplicity requirement of mobility network models.

3.2 Network assumptions of the WBAN and human body mobility

In most situations, the human body and its clothing serve as the WBAN carrier. One important feature of WBAN is that it comprises both node-group and single-node relative movements, which is unique to the WBAN relative to other mobile networks.

In this study, we built an HMM based on a steady walking pace or a slow running speed, and we did not consider the transition between states, such as a sudden fall or sitting. Below, we summarize the features of human body mobility considered in this model, while the speed of the network movement remains relatively constant.

(1) Each node moves around the body trunk and the chest is the center of all movements. The movement radius is less than 2 m.

(2) The sink node located in the body trunk is fixed and its movement does not change the network topology. Nodes in the head are also fixed.

(3) Compared with those on the trunk and head, nodes on the arms and legs greatly change the network topology. With respect to the abovementioned features, our assumptions are as follows:

(1) The sink node is located in the center of the chest.

(2) Sensor nodes in the WBAN are arranged in a symmetrical configuration.

(3) The walking or running speed ranges from 0 to 10 m/s without any pauses.

(4) To simplify the model, in the network topology, we consider only the nodes located on the elbows and legs.

3.3 Formulation of human mobility model

In the two-dimensional Cartesian coordinator shown in Fig. 1, $N_{SN}$, $N_{RE}$, $N_{LE}$, $N_{RK}$, and $N_{LK}$ are the five key nodes, where SN, LE, RE, LK, and RK are the sink node, left elbow, right elbow, left knee, and right knee, respectively.

The sink node is regarded as the origin of the coordinates. In the three-dimensional Cartesian coordinates shown in Fig. 2, the coordinates of the five key nodes are as follows: $(0, y_{SN}, z_{SN}), (0, y_{LE}, z_{LE}), (0, y_{RE}, z_{RE}), (0, y_{LK}, z_{LK}), (0, y_{RK}, z_{RK})$.

Suppose the initial state of the human body is static, then the initial coordinate matrix for the WBAN is $S_0$. The three-dimensional Cartesian coordinates of the key nodes

\[
\begin{align*}
N_{SN} &:= (0, y_{SN}, z_{SN}) \\
N_{LE} &:= (0, y_{LE}, z_{LE}) \\
N_{RE} &:= (0, y_{RE}, z_{RE}) \\
N_{LK} &:= (0, y_{LK}, z_{LK}) \\
N_{RK} &:= (0, y_{RK}, z_{RK})
\end{align*}
\]

Fig. 1 Two-dimensional coordinates of key nodes.
are expressed by matrix $S_0$, as shown in Eq. (6), below:

$$
S_0 = \begin{bmatrix}
    x & y & z \\
    0 & 0 & 0 \\
    y_{LE} & z_{LE} & 0 \\
    -y_{LE} & z_{LE} & 0 \\
    y_{LK} & -z_{LK} & 0 \\
    -y_{LK} & -z_{LK} & 0 \\
\end{bmatrix}
$$

(6)

3.4 State transfer of human walking or slow running

As shown in Fig. 3, the nodes can be used to illustrate the walking (or slow running) process. Although the human-body walking process is continuous, in this model, it is characterized as comprising four discrete steps, as shown by the three-dimensional coordinator in Fig. 3. After completing the four steps, the nodes on the elbows and knees return to the initial state. As such, the movement of the nodes is a cyclical process, wherein $D_E$ represents the magnitude of the distance of the arm swing from the coordinator (along the $x$ axis), $D_K$ is the magnitude of each stride, and $M(n)$ is the model mode of each step in the walking process, where

$M(0)$: Elbows are down, and knees are approximately straight.

$M(1)$: Left elbow and right knee are forward and right elbow and left knee are back.

$M(2)$: Left elbow and right knee are back and right elbow and left knee are forward.

$M(n)$ is represented as a matrix, as shown in Eq. (6), (7), and (8), where $M(0) = S_0$, and

$$
M(1) = \begin{bmatrix}
    x & y & z \\
    0 & 0 & 0 \\
    y_{LE} & z_{LE} & -y_{LE} \\
    -y_{LE} & z_{LE} & -y_{LE} \\
    y_{LK} & -z_{LK} & -y_{LK} \\
    -y_{LK} & -z_{LK} & -y_{LK} \\
\end{bmatrix}
$$

(7)

$$
M(2) = \begin{bmatrix}
    x & y & z \\
    0 & 0 & 0 \\
    -y_{LE} & z_{LE} & y_{LE} \\
    y_{LE} & z_{LE} & -y_{LE} \\
    -y_{LK} & -z_{LK} & y_{LK} \\
    y_{LK} & -z_{LK} & -y_{LK} \\
\end{bmatrix}
$$

(8)

State transformation diagram is used to simulate the walking process, as shown in Fig. 4. Supposing the time from one state to the next is $T$ ($n$ is typically used to indicate time in discretization systems), then the state will return to the initial state after $4T$.

In the walking simulation, each displacement, arm swing, and leg stride is essentially constant but there is also deviation from the mean value. To maintain balance, if the walking displacement is great, the magnitude of both arm swings will also increase, as will the stride of both legs, and vice versa. $\sigma_E$ indicates the greatest arm-swing

![Fig. 4 State transformation diagram of human regular steady movements.](image-url)
magnitude variation, and $\sigma_E \in [\sigma_{Ena}, \sigma_{Em}]$. $\sigma_K$ indicates the greatest stride variation, and $\sigma_K \in [\sigma_{Kn}, \sigma_{km}]$. $\theta$ is the angle between the velocity and $yz$ plane. $\gamma$ is the angle between velocity and $xy$ plane. Matrix $H$ represents the variation in node locations from the sink node. $H$ is given in Eq. (10).

$$H(n) = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{cases} M(0), & n = 4i \pm 2, (i = 1, 2, 3 \ldots) \\ M(1), & n = 4i + 1, (i = 0, 1, 2 \ldots) \\ M(2), & n = 4i + 3, (i = 0, 1, 2 \ldots) \end{cases}$$

(9)

By the description in the previous section, the matrix $B$ of the state transfer mathematics model for human walking is shown in Eq. (10), as follows:

$$B = M(n) + H(n), n = 0, 1, 2 \ldots$$

(10)

where

$$M(n) = \begin{cases} M(0), & n = 4i \pm 2, (i = 1, 2, 3 \ldots) \\ M(1), & n = 4i + 1, (i = 0, 1, 2 \ldots) \\ M(2), & n = 4i + 3, (i = 0, 1, 2 \ldots) \end{cases}$$

3.5 Construction of random BGMM

We introduced the RGMM model in Section 2 and constructed a simplified HMM in Section 3.4 above. By extending the RGMM model into a group mobility model by combining it with an HMM, we construct and propose a new model in this section, which we call the random Gauss–Markov:

$$S_n = S_{n-1} + V_{n-1} + M(n) + H(n).$$

Then by using Eq. (1), we can also express $S_n$ as in Eq. (11).

$$S_n = S_0 + \sum_{i=0}^{n-1} V_i + \sum_{i=0}^{n-1} M(n) + \sum_{i=0}^{n-1} H(n) =$$

$$S_0 + \left(1 - \alpha^n \right) v_0 + \left(1 - \alpha^n - \frac{1}{1 - \alpha} \right) \mu +$$

$$\sigma(\sqrt{1 - \alpha})^2 \sum_{j=0}^{n-1} \sum_{i=0}^{n-1} \alpha^{i-j} w_j + \sum_{i=0}^{n-1} M(n) + \sum_{i=0}^{n-1} H(n)$$

(11)

The $\theta$ and $\gamma$ is expressed as

$$\theta_n = \alpha \theta_{n-1} + (1 - \alpha) \mu_0 + \sigma_\theta(\sqrt{1 - \alpha}) w_{\theta_{n-1}},$$

$$\gamma_n = \alpha \gamma_{n-1} + (1 - \alpha) \mu_1 + \sigma_\gamma(\sqrt{1 - \alpha}) w_{\gamma_{n-1}},$$

(12)

The coordinator of each node is given by following equations.

$$x_n = x_{n-1} + |s_{n-1}| \cos \gamma_{n-1} \cos \theta_{n-1}$$

$$y_n = y_{n-1} + |s_{n-1}| \cos \gamma_{n-1} \sin \theta_{n-1}$$

$$z_n = z_{n-1} + |s_{n-1}| \sin \gamma_{n-1}$$

(13) (14) (15)

From Eq. (11), we can see that the BGMM model is directly related to the initial locations and velocities of the nodes, the expected velocity, memory level $\alpha$, the walking (or running) state $M(n)$, and the deviation of each stride or arm swing $H(n)$. In the theoretical expression, both the human body movement and its previous state are taken into consideration.

4 Simulation and Results

4.1 Initialization of the BGMM

In the BGMM model, $\alpha$ has the same meaning as that in the RGMM model—the degree of correlation between the current and previous velocities. If $\alpha = 0$, RGMM is a random Gauss process. If $\alpha = 1$, it moves at a constant speed. The BGMM model is oriented to human movement, so its movement patterns seldom have sharp turns or sudden stops. To obtain a suitable value of $\alpha$, first, we use Matlab 7.11 to simulate the traces of the movements of the nodes for different values of $\alpha$. In the simulations, we used the networking parameters shown in Table 2.

Next, we simulated two mean speeds, where $\mu_v = 1$ m/s is regular walking speed and $\mu_v = 4$ m/s is regular slowly running speed. For each mean speed, four different memory level $\alpha$ are simulated, which is corresponding to the degree of memory $\beta = \left\{10^0, 10^{0.5}, 10^{-1}, 10^{-2}\right\}$. These value of $\beta$ is typical degree of memory in stochastic processes.

Because the layout of the key nodes in the BGMM model is symmetrical, only the traces of the movements of $N_{SN}$, $N_{RE}$, and $N_{LK}$ are shown in simulations results.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>5</td>
</tr>
<tr>
<td>$T$</td>
<td>$\in {300, 20}$</td>
</tr>
<tr>
<td>$\mu_v$</td>
<td>${1 \text{ m/s}, 4 \text{ m/s}}$</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>$\frac{1}{3} \mu_v$</td>
</tr>
<tr>
<td>$\mu_\theta$</td>
<td>0.2</td>
</tr>
<tr>
<td>$\sigma_\theta$</td>
<td>0.05</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>${0.37, 0.73, 0.9, 0.99}$</td>
</tr>
</tbody>
</table>
The human movement along the z-axis is almost steady. To simplify the simulation, the slight change along the z-axis is included in the simulations. Thus, the horizontal and vertical axes are x-axis and y-axis, respectively, in Figs. 5, 6, and 7. The trace of the nodes shown in these three figures are two-dimensional.

Figures 5 and 6 show the traces of the movement of key nodes at $\mu_v = 1 \text{ m/s}$ and $\mu_v = 4 \text{ m/s}$ with 300 time slots duration. In order to observe the position change between adjacent time slots, the traces of the movements of key nodes during 20 time slots are also given in Fig. 7.

In 20 time slots, the neighbor trace is shown in Figs. 5 and 6. The traces of the movements in Figs. 5a and 5d, and Figs. 6a and 6d are smoother than that in Figs. 5b and 5c and Figs. 6b and 6c, but there are sharp turns between the adjacent instants in Fig. 7a. When $\alpha \in [0.9, 0.99]$, the traces of the movements of the nodes are similar to human movements in that they are smooth and there are no sharp turns. From Figs. 5 and 6, we can also see that the speed has no great impact on the traces of the movements. With increased speed, the traces of the movements of $N_{SN}$, $N_{RE}$, and $N_{LK}$ in Fig. 7 tend to coincide. In the next section, we choose 0.95 as the value of $\alpha$ to simulate four different metrics.

### 4.2 Simulation results for direct metrics of the BGMM

Mobility metrics are used to describe the features of different mobility patterns. These metrics can be used to analyze the impact of the models on the performance of communication networks. Mobility metrics can be divided into two categories. Direct mobility metrics include but are not limited to the average link duration, average relative speed, average temporal dependency, average spatial dependency, and pause time. Derived mobility metrics are developed based on the direct metrics to represent generic network performances. Derived mobility metrics include link-based metrics, path-based metrics, node connectivity, network connectivity, and quality service, to name a few [3, 10, 26, 27].

In this study, we used the following metrics: Average Link Duration (ALD), Average Relative Speed (ARS), Average Temporal Dependency (ATD), and Average...
Spatial Dependency (ASD) to evaluate the BGMM model. We based the BGMM model on the RGMM model. The NCM model is very similar to the BGMM model in that they are both group mobility models and the nodes all move around a reference node. So, here, we compare the simulation performances of the BGMM, RGMM, and NCM models.

In the simulations, we generated scenarios for speeds of 1, 2, 3, . . . with 10 as the maximum speed, because the fastest human running speed is about 10 m/s. The number of nodes is five, which corresponds with the five key nodes described in Section 3.3. The duration of each scenario is 300 seconds. The memory level $\alpha = 0.95$.

4.2.1 ALD

ALD indicates the period during which the links are stable. This parameter specifies the longest interval of time between nodes $i$ and $j$, thus forming the link $(i,j)$. The ALD is determined as shown in Eq. (16).

$$ALD = \frac{\sum_{t=0}^{T} \sum_{i=1}^{N} \sum_{j=i+1}^{N} LD(i,j,tl)}{(T+1) \frac{(N-1)N}{2}},$$

and $LD(i,j,tl) \neq 0$

$N$ is the number of nodes in the networks, $LD$ is the longest time interval between nodes $i$ and $j$, and $T$ is the duration.

In Fig. 8, the ALD of the RGMM model is the shortest. Because the nodes in the RGMM move independently, each node independently determines the speed and direction of the next instance, which also greatly impacts the topology. This explains why the ALD of RGMM model is the shortest. The ALD of the BGMM model is similar to that of the NCM model. Because these two models are both group mobility models and their nodes move around the reference node, their topologies are stable. In the BGMM model, the movement of nodes is limited by human mobility. In the NCM model, the movement of nodes is random. So, the ALD of the BGMM model is slightly greater than that of the NCM model.

4.2.2 ARS

The average relative speed is expressed as the relative speed of all pairs of nodes in the networks. Assume that $S(i,t)$ and $S(j,t)$ are the locations of nodes $i$ and $j$ at time $t$, respectively. Then the relative speeds of $i$ and $j$ are defined as in Eq. (17).

$$V(i,j,t) = \frac{d(|S(i,t) - S(j,t)|)}{dt}$$

In this paper, we define the ARS over time as follows:

$$ARS_{i,j} = \frac{1}{T} \int_{0}^{T} |V(i,j,t)| dt,$$

$$ARS = \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} |S(i,t_0 + T) - S(j,t_0 + T)|}{T \cdot N(N-1) / 2}$$

In Fig. 9, we can see that the ARS of the RGMM model is much greater than those of the BGMM and NCM models due to the independent movement of each node in the RGMM model. Nodes in the BGMM and NCM models move around their reference nodes. Their relative speeds are also restricted by the speed of the reference nodes. The topology control algorithm in the NCM model limits the distance between the reference node and other nodes, so the ARS of NCM model is the slowest.

4.2.3 ATD

ATD, which is the degree of temporal dependence, indicates how an individual node changes its velocity with time. This parameter reflects whether its current velocity is dependent on the previous velocity. In another words, it shows the smoothness of the mobility model. The temporal
dependence for a single node between instances $i$ and $j$ is defined as shown in Eq. (19).

$$TD_{ij} = \frac{\vec{v}(i) \cdot \vec{v}(j)}{||\vec{v}(i)|| \cdot ||\vec{v}(j)||}$$

where $\vec{v}(i)$ and $\vec{v}(j)$ are speed vectors of the same nodes at $t_i$ and $t_j$ instance.

The average temporal dependence can be obtained from Eq. (19), and given in Eq. (20).

$$ATD = \frac{\sum_{i=1}^{T} \sum_{j=1}^{N} \sum_{j=i+1}^{N} TD_{ij}}{\text{Total}}$$

$$\text{Total} = T \cdot \frac{N(N-1)}{2};$$

$$ATD = \frac{\sum_{i=1}^{T} \sum_{j=1}^{N} \sum_{j=i+1}^{N} TD_{ij}}{T \cdot \frac{N(N-1)}{2}}$$  (20)

Figure 10 shows that the ATDs of the RGMM and BGMM models are much greater than that of the NCM model. The RGMM and BGMM models are constructed based on the Gauss–Markov process, in which parameter $\alpha$ is used to indicate the correlation of the speed between $n$-th and $(n-1)$-th instances. In the NCM, the speed of the node has no correlation with the speed at different times.

In Fig. 11, we see that the ATD of the BGMM model increases with increases in $\alpha$. Thus, when $\alpha = 0$, the ATD of the BGMM model will be similar to that of the NCM model.

4.2.4 ASD

The ASD is the degree of correlation of the movement pattern of a node with that of another node in its neighborhood. This reflects the smoothness of a mobility model. Equation (21) defines the spatial dependence between nodes $i$ and $j^{[29]}$.

$$SD_{ij} = \min(v_i, v_j) \cdot \max(v_i, v_j);$$

where $\theta_{ij}$ is the angle between the velocity of nodes $i$ and $j$. The average spatial dependence can be obtained using Eq. (22).

$$ASD = \frac{\sum_{i=1}^{T} \sum_{j=1}^{N} \sum_{j=i+1}^{N} SD_{ij}}{\text{Total}}$$

$$\text{Total} = T \cdot \frac{N(N-1)}{2};$$

$$ASD = \frac{\sum_{i=1}^{T} \sum_{j=1}^{N} \sum_{j=i+1}^{N} SD_{ij}}{T \cdot \frac{N(N-1)}{2}}$$  (22)

As we can see in Fig. 12, the ASD of the BGMM model is much greater than that of the RGMM model. The relationship between the nodes and reference node in the BGMM model is constrained by size of the human body. The ASD of the BGMM model is similar to that of the NCM model, because they are both limited by the reference node. Figure 12 also shows that a change in the ASD is not directly related to maximum speed.

From the simulations and the above analysis, we can
see that the four direct metrics of the BGMM model are better than those of the RGMM model for simulating human movement. The direct metrics of the BGMM model, excluding the ATD, are similar to those of the NCM model. We can conclude that the BGMM model has the advantages of a group mobility model as well as that of RGMM entity models that do not generate sharp turns.

5 Conclusion

In this paper, we have made a number of contributions to the development of a WBAN mobility model. We propose a new model that portrays the main position features of WBAN node movements. We analyzed the state transfers of regular and steady human movements and constructed a mathematical mobility model. We developed a new mobility model called the BGMM model, which is oriented to WBANs in that it takes human body movement into consideration. The simulation results show that the new mobility model demonstrates better performance with respect to direct mobility metrics and effectively represents WBAN movement. In future work, we will apply real-world datasets in simulations and use the derived metrics to evaluate the performance of the BGMM model.

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References

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