Optimized Handover Strategy with Movement Trend Awareness for Body Sensor Networks

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Abstract

When a Body Sensor Network (BSN) that is linked to the backbone via a wireless network interface roams from one coverage zone to another, a handover is required to maintain network connectivity. This paper proposes an optimized BSN handover strategy which utilizes the movement trend of the BSN wearer and makes handover decisions based on the estimated future position of the user. Simulation results indicate that outage probability can be reduced by the proposed approach while unnecessary handover rate remains similar compared to that of the conventional methods. In addition, no extra equipment is needed for the proposed method.

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1. Introduction

Body Sensor Networks (BSNs) enable continuous, non-intrusive, and remote health monitoring, and are widely considered as the next generation of healthcare technology [1]. Communication issues involved in BSNs consist of two categories, intra-BSN referring to the communication between body sensors and a portable personal server (e.g. [2] [3]) and inter-BSN referring to the communication from BSNs to network interfaces [4]. This paper addresses the inter-BSN communication issues, namely, the handover problem for BSNs. For instance, when a BSN user wanders inside a hospital while delivering
the physiological information to doctors via wireless local area networks (WLANs), handover has to be handled from one network interface to another in order to ensure the continuity of the communication.

There exist some special features for communications in BSNs. On the one hand, the information transmitted in a BSN is life-critical and real-time, thus outage probability and transmission delay should be strictly reduced. On the other hand, some intrinsic characteristics of a BSN user such as movement intention, pattern, and constraints sensed by inertial sensors can be easily accessed in most BSNs, and thus can be taken into consideration to help make handover decision. Consequently, communication methods can be further developed by taking advantage of these special features to meet the stringent requirements for BSNs.

Conventional handover approaches have been mostly developed by cellular network researchers [5], in which the Received Signal Strength (RSS) is commonly used as a metric. In [6], the RSS from the serving Base Station (BS) is compared with that from a target BS, and decisions are made using a constant margin. However, the fluctuations of RSS associated with shadow fading cause a call to be repeatedly handed over back and forth between neighboring BSs, in what is called the “ping-pong effect” [7]. To suppress the ping-pong effect, several location-based handover algorithms have been proposed in [7], [8], [9] using timers or hysteresis. However, most of the position prediction method applied is quite preliminary. For example, most studies assume that the location of the mobile can be determined using the Global Positioning System (GPS), but GPS is actually unavailable in indoor environments. Moreover, most prediction methods only estimate one time interval forward. It has been noticed that if the future trajectory of the mobile station can be achieved over a relatively longer period, handover performance can be further improved.

Based on the above observations, we propose an optimized handover strategy, which utilizes movement trend to predict the future trajectory of a BSN user over a relatively longer period. Based on the trend estimation, a theoretical analysis is investigated so as to develop the optimal handover strategy. The objective of the proposed handover strategy is to reduce outage probability while keeping the handover rate similar to that of conventional methods.

The contributions of this paper are threefold. First, the human movement trend is taken into account to help with the handover problem. A real-time user profile based on movement trend is built for each BSN user, which provides a guideline for future design of communication issues on BSNs. Second, confidence probability of position estimation is proposed to theoretically measure the accuracy of the prediction, while most other algorithms analyze performance only experimentally. Third, a handover strategy is proposed to optimize the performance improvement.

The rest of paper is organized as follows. Section 2 explains the detail design of the proposed handover strategy, while the simulation results and discussions are shown in section 3. Section 4 draws the conclusions.

2. Proposed Handover Strategy

A common scenario of BSN is utilized in our proposed method. The physiological information collected by body sensors is forwarded through a portable personal server to an access point (AP). The AP can then forward the information to the target system or end-user. Our proposed handover strategy is implemented on the portable personal server of a BSN, when the BSN user roams from one AP’s coverage zone to another.

The proposed handover strategy comprises four steps, viz. trajectory tracking, position prediction, formulation of confidence probability, and handover initiation.
2.1. Trajectory Tracking

The historical trajectory of the BSN wearer is achieved by data fusion of inertial sensor-based kinematic tracking and WLAN RSS-based tracking. Kinematic tracking adopts kinematic relationships based on data accumulated by inertial sensors, while WLAN RSS-based localization method is based on the RSS readings of the portable personal server. A Kalman filter [10] is used as the fusion tool to improve the positioning accuracy, and more importantly it provides the real time velocity information which is to be utilized in position prediction.

The state vector of the Kalman filter is expressed as \( X_k = [s, v, a]^T \), where \( s, v, a \) are the target position, velocity, and acceleration respectively. Each of them is a two-dimensional vector along x-axis and y-axis, i.e. \( s = [s_x, s_y]^T \), \( v = [v_x, v_y]^T \), \( a = [a_x, a_y]^T \). The system state transition function of the filter can be expressed as,

\[
X_k = F_k X_{k-1} + w_k
\]  

where \( F_k \) is the state transition matrix, determined by the mobility model. We utilize the Wiener-process acceleration model (WPAM) described in [11], which assumes that the acceleration is a Wiener-process. \( w_k \) is the process noise which is determined empirically. This state transition function performs the kinematic tracking.

The measurement vector \( z_k = [s, a]^T \) is obtained by a WLAN RSS-based Horus system [12] for \( s \), and readings from the inertial sensors for \( a \) respectively. The observation equation is

\[
z_k = H_k X_k + n_k
\]  

where \( H_k \) is the observation matrix, and \( n_k \) is the measurement noise that is determined empirically. Due to multipath fading and shadowing, RSS-based handover do not always perform well. From the output of the Kalman filter, a relatively accurate historical trajectory of the user could be achieved.

2.2. Position Prediction

Based on the historical trajectory, a series of future position predictions can be made and they are denoted as \( s_i, k < i \leq k + \tau \), where \( \tau \) is the prediction period. Assuming that human trajectory would follow some trend with high possibility, the movement trend could be utilized to predict positions over a relatively longer period.

In this paper, we utilize the average velocity \( \bar{v} \) over the last \( N \) time slots of the historical trajectory as the movement trend. It can be expressed as,

\[
\bar{v} = \frac{v_{k-1} + v_{k-2} + \ldots + v_{k-N}}{N}, \quad k > N
\]
where \( [v_{k-1}, v_{k-2}, \ldots, v_{k-N}] \) is the set of historical velocities, and \( k \) represents the current time index.

To model future positions, the following rules are applied:

- The future trajectory still follows the WPAN model [11].
- \( \bar{v} \) is used as the starting velocity.
- The white Gaussian acceleration noise is denoted as \( a_i \sim N(0, \sigma_a^2) \), where parameter \( \sigma_a^2 \) is extracted from the historical accelerations by taking their variances, i.e. \( \sigma_a^2 = \text{var}[a_{k-1}, a_{k-2}, \ldots, a_{k-N}] \).

Thus we have,

\[
v_i = v_{i-1} + a_i T, \quad k < i \leq k + \tau, \quad v_k = \bar{v}
\]

\[
\Delta s_i = \sum_{j=k}^{i-1} \left( \frac{v_{j-1} + v_j}{2} \right) T = (i-k)T \bar{v} + \sum_{j=k}^{i-1} T \left[ (i-j) + \frac{1}{2} \right] a_j
\]

\[
s_i = s_k + \Delta s_i
\]

where \( v_i \) is the predicted velocity at time index \( i \), \( T \) is the time interval between two prediction, \( s_i \) is a random variable that models the future position, and \( \Delta s_i \) is the position vector pointing from \( s_k \) to \( s_i \). After that, \( s_i, k < i \leq k + \tau \) are given by taking the expectation over \( s_i \),

\[
\tilde{s}_i = E(s_i) = E(s_k + \sum_{j=k}^{i-1} \left( \frac{v_{j-1} + v_j}{2} \right) T) = s_k + (i-k)T \bar{v}
\]

Eqn. (7) is a linear increasing function of time and the coefficient is determined by \( \bar{v} \), which makes sense as \( \bar{v} \) carries the prediction information by indicating both the movement trend and average speed in our strategy. As shown in Figure 1, curve AC is the actual trajectory. When the BSN user crosses the APs boundary at point B, position prediction is performed and the line BD is the predicted trajectory. \( \hat{s}_{k+1}, \hat{s}_{k+2}, \hat{s}_{k+3} \) are the predicted positions.

![Figure 1. Position prediction.](image-url)
2.3. Formulation of Confidence Probability

In order to adjust the handover strategy according to the position prediction, we propose a metric to measure the accuracy of prediction, i.e. the confidence probability. The confidence probability $\Pr_{\text{con}}(i)$ is defined as the conditional probability that at time index $i$ the user is actually within coverage of the target AP, conditioned on the user being predicted to be within the coverage of the target AP.

As can be seen from Eqn. (4) to Eqn. (7), the predicted position $s_i$ follows a Gaussian distribution $s_i \sim N(\hat{s}_i, \sigma_i^2)$. The position variance is decomposed along the parallel and orthogonal directions to the boundary of the two APs. It is noticed only the orthogonal factors in the predicted position contribute to the final decision of our handover strategy. Denoting $P$ as the mapping vector that is orthogonal to the APs boundary, position and its variances involved in this section should be projected along $P$. Then the confidence probability can be expressed as,

$$\Pr_{\text{con}}(i) = 1 - Q\left(\frac{\Delta\hat{s}_i}{\sigma_i}\right)$$

where $Q(\bullet)$ is the Gaussian Q-function defined in [13], $\Delta\hat{s}_i$ is the distance between the predicted position $s_i$ and APs boundary, $\sigma_i$ is the standard deviation of $s_i$ in Eqn. (6) along $P$. $\Delta\hat{s}_i$ and $\sigma_i$ are calculated as follows,

$$\Delta\hat{s}_i = (\hat{s}_i - s_k)P = (i - k)\hat{v}P$$

$$\sigma_i^2 = E[P^T(s_i - E[s_i])^2P] = P^T\sigma^2_{s_i}P + \frac{(i - k)^2 T^2}{4} P^T\sigma^2_{\nu}P$$

where $\sigma^2_{\nu}$ is the uncertainty of the current point $s_k$, which is the Kalman filter variance. As can be observed, $\Delta\hat{s}_i / \sigma_i$ in Eqn. (8) increases with $i$, thus $\Pr_{\text{con}}(i)$ also increases with $i$. This means that the farther the user’s predicted position is from the boundary of the serving AP, the higher the probability that the user is actually within the coverage of the target AP, as illustrated in Figure 2. However, prediction period should remain within the tolerable period $\tau$ so that the assumptions are valid. This confidence probability can help to adjust the handover strategy in relation to the position prediction.

![Figure 2. Confidence probability prediction](image-url)
2.4. Handover Initiation

Based on the position prediction, we propose a handover initiation approach to determine which time index in the near future is optimal to perform handover. The determination of handover initiation time is a tradeoff problem. On the one hand, it is intuitive to observe that the unnecessary handover rate decreases when handover is delayed. On the other hand, if the handover time is delayed too much, communication would suffer from low signal-to-noise ratio (SNR), which increases outage probability. Thus the determination of handover time should meet the unnecessary handover rate requirement and the outage probability requirement concurrently.

A handover from AP1 to AP2 occurs at time index \( i \) if the following two criteria are satisfied,

\[
\text{Criterion 1: } 1 - \Pr_{\text{con}}(i) \leq \alpha \\
\text{Criterion 2: } \Pr_{\text{outage}}(i) \leq \beta
\]

where \( \alpha \) is the maximum required unnecessary handover rate and \( \beta \) is the maximum tolerable drop call probability. Criterion 1 is to ensure the unnecessary handover rate requirement. The unnecessary handover rate \( P_{\text{eff}}(i) \) at time index \( i \) can be expressed in terms of \( \Pr_{\text{con}}(i) \) as \( P_{\text{eff}}(i) = 1 - \Pr_{\text{con}}(i) \).

Criterion 2 is to ensure the outage probability requirement. As shown in Figure 3 (a), \( \hat{s}_{i,\min} \) is the point where the criterion 1 is met, \( \hat{s}_{i,\max} \) is the point where the criterion 2 is met. Thus any \( i_{\text{opt}} \in [\hat{s}_{i,\min}, \hat{s}_{i,\max}] \) satisfies the two criteria concurrently. If \( i_{\text{opt}} \) is chosen closer to \( \hat{s}_{i,\min} \), the outage probability could be further reduced, which is shown as Outage Gain in Figure 3 (a). Conversely, if \( i_{\text{opt}} \) is closer to \( \hat{s}_{i,\max} \), the handover rate could be further reduced, which is shown as HR Gain in Figure 3 (a). Considering that the outage is crucial for BSNs, we choose the point \( i_{\text{opt}} = \hat{s}_{i,\min} \) as the optimal handover initiation time.

The overall flow chart of our proposed approach is shown as Figure 3 (b). When the BSN user crosses the APs boundary, the handover strategy is initiated to output an optimal handover time. Then the BSN user waits until the handover time to perform the handover process as long as the actual position is still within the acceptable range. The acceptable range is the area where the outage probability requirement can be met. Otherwise, the handover process is initiated immediately.

Figure 3. (a) Performance Gain; (b) Flow chart for proposed handover strategy
3. Simulation Results and Discussion

3.1. Simulation Set Up

The simulation scenario is that a BSN wearer wanders in an area covered by a WLAN, commonly based on an IEEE 802.11a/b/g/n network. We suppose that the layout for the WLAN APs follow traditional hexagonal layout with each AP coverage radius of 50 meters, and the proposed handover strategy is simulated in Matlab 7.0. The BSN user is assumed to travel for 100 seconds following the mobility model of WPAM [11]. Each simulation is run for 1000 iterations to alleviate the effect of simulation randomness.

Two performance metrics utilized are the handover rate and outage times. Since each handover requires network resources to reroute the call to the new AP, which would cause switching load, it is significant to reduce handover rate, especially for BSNs where energy is strictly limited. Outage degenerates the quality of service (QoS) below an acceptable level, and increases the co-channel interference as well. For BSNs where life-critical information is transmitted, it is crucial to decrease drop call times.

The simulation results are compared with two conventional methods, i.e. a basic scheme and hysteresis-based handover in the same setup. The basic scheme refers to the handover that is performed once the user crosses APs boundary, while hysteresis-based handover refers to the handover that is not performed until the hysteresis distance requirement is satisfied.

3.2. Results and Discussion

By performing the Kalman filter tracking algorithm described in section 2.1, the positioning accuracy achieves significant improvement compared to that of only WLAN RSS-based tracking. Figure 4 shows the location errors’ Cumulative Distribution Function (CDF) of the Kalman filter tracking and RSS-based tracking. As expected, for our proposed handover, 90% of the location errors are within 2.5 meters, while that of RSS-based tracking stays within 3.5 meters.

The handover performance is investigated under different hysteresis margins. For the proposed handover method, hysteresis margin refers to the distance between the APs boundary and the position where the outage requirement is met. By changing the hysteresis margin, the outage requirement is also changed. The results are shown in Figure 5.

![Empirical CDF comparison of Kalman filter output and RSS-based tracking](image)

Figure 4. Empirical CDF comparison of Kalman filter output and RSS-based tracking
Instead of showing the actual number of handovers performed for these three schemes, the handover rates are presented in Figure 5 (a), which are normalized by the number of handovers from the basic scheme. As expected, the handover rate of the hysteresis-based scheme keeps on decreasing as the hysteresis margin gets larger. For the proposed scheme, the handover rate also decreases and remains similar to that of the hysteresis-based scheme when the hysteresis margin is relatively small. It can be explained by the increasing chance to meet the confidence requirement (Criterion 1) of the strategy when the hysteresis margin increases, and thus there is a trend of decreasing the handover rate by avoiding unnecessary handover. When the hysteresis margin gets larger, there is enough space for the confidence requirement (Criterion 1) to be achieved most of the time and the handover rate remains stable as shown in Figure 5 (a) since most of the unnecessary handovers have been alleviated.

Figure 5 (b) shows the comparison of the outage times versus the hysteresis margin. Outage times are counted for the 1000 iterations. It is observed that the outage times of the basic scheme are lower than the other two approaches. However, it is at the expense of much higher handover rate as shown in Figure 5 (a). The drop call times of our proposed method significantly outperforms that of hysteresis-based handover, especially when the hysteresis gets larger. This is because as long as the BSN user is predicted to enter another AP with high confidence probability, the handover process would be handled immediately rather than wait until the hysteresis threshold is achieved, which leads to higher risk of dropping a call.

We also analyze the effect of different location errors on the proposed handover performances. The results are shown in Table 1. It can be seen that within tolerable error range the proposed handover performance changes slightly with location errors, which shows the robustness of our algorithm. This is because our algorithm is mainly based on the movement trend and user profile, which is extracted from a large volume of historical data. Thus the effect of relatively large variance can be substantially alleviated.

Table 1. Proposed handover performance versus location error

<table>
<thead>
<tr>
<th>Location Error (m)</th>
<th>Handover Rate</th>
<th>Drop Call Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.82</td>
<td>0.7532</td>
<td>15</td>
</tr>
<tr>
<td>1.21</td>
<td>0.7845</td>
<td>16</td>
</tr>
<tr>
<td>1.62</td>
<td>0.7947</td>
<td>15</td>
</tr>
<tr>
<td>2.01</td>
<td>0.8062</td>
<td>17</td>
</tr>
</tbody>
</table>
Conclusion

In this paper, an optimized handover strategy for BSNs is proposed. With significant performance improvement demonstrated, we reach three concluding inferences: first, the human movement trend information sensed by BSNs can be utilized to build real-time individual profile to predict future trajectory. Second, the statistical confidence of position prediction can be used as a theoretical guideline to facilitate handover planning. Third, prediction over relatively longer period provides optimized solution for the handover problem. In addition, no extra equipment is needed for our proposed method.

It has been shown that the average velocity is a simple and effective way to reflect a user’s movement trend. More complex movement trend would be investigated in our future work. Moreover, the proposed handover strategy is not limited to BSNs. As long as there are accelerometers available, our proposed algorithm can be adopted. However, caution should be exercised in utilizing the average velocity to build the user movement profile, and drop call probability may not be so crucial for other applications.

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