Badminton Stroke Recognition Based on Body Sensor Networks

Zhelong Wang, Ming Guo, and Cong Zhao

Abstract—**A badminton training system based on body sensor networks has been proposed. The system may recognize different badminton strokes of badminton players. A two-layer hidden Markov model (HMM) classification algorithm is proposed to recognize 14 types of badminton strokes. In the first layer, we use acceleration magnitude of the right wrist to determine a threshold to detect strokes, and then, the HMM is applied to filter out nonstroke motions. In the second layer, we adopt the HMM to classify all the strokes into 14 categories. Experimental results show that the two-layer HMM can achieve good recognition accuracy. The effectiveness and feasibility of the two-layer HMM classification algorithm have been verified in a comparison.**

Index Terms—**Badminton stroke recognition, body sensor networks (BSN), hidden Markov model (HMM).**

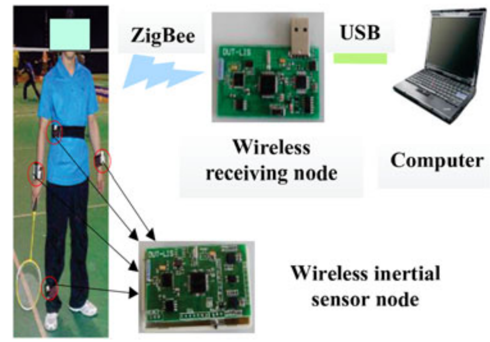

Fig. 1. Sensor placement and system platform.

I. Introduction

Body sensor networks (BSN) [1]–[3] have been applied in recognition of sport activities [4], detecting martial motion sequences [5], automatic video annotation and automatic generation of highlights [6], and performance sports [7].

With respect to badminton sport, all of the badminton strokes rely on the wrist. It requires badminton players to be extremely agile.

Kwan, Andersen, Cheng, Tang, and Rasmussen [8] use a motion capture system to measure motion signals of a badminton racket, and the system is used to assess the performance of players in different skill levels. Jainter and Gawin [9] utilize three sensor nodes placed on the right upper arm, right lower arm, and racket to explore the relativities among racket speed, shuttle ball speed, and arm speed when a badminton smash is performed. In another study, Jainter and Gawin [10] explore the differences of badminton smash in shuttle speed, arm speed, and racket speed between international and national elites. Kiang, Yoong, and Spowage [11] use a single accelerometer and an acoustic sensor to analyze the relationship between racket speed and shuttle ball speed. Tian [12] utilizes inertial sensors, electrocardiogram, and blood oxygen monitor to measure vital signals of badminton players and recognize activities of players on the court, such as standing, lying, running, walking, etc. The research studies above have largely focused on the performance analysis of a badminton smash motion but not recognize different badminton strokes.

This paper proposes a badminton stroke recognition process and a badminton training system based on BSN. We intend to apply the system in a realistic training environment or a real game with a primary focus on the recognition of badminton strokes, which can play an important role for players. The players can get the real-time feedback by using the system to improve the training quality, for example, they can distribute physical fitness reasonably by estimating the number of high-intensity strokes.

The organization of this paper is as follows. Section II describes the system platform and data collection methods. Section III describes the badminton stroke recognition methodology. Section IV presents the evaluation. Section V presents the conclusion.

II. System Platform and Data Acquisition

The proposed badminton training system includes a wireless receiving node, four wireless inertial sensor nodes, and a personal computer (PC) (see Fig. 1). We use the system to collect motion signals of badminton players and recognize different badminton strokes. Each wireless inertial sensor node is comprised of a triaxial accelerometer ADXL326, a single-axis gyroscope LY550, and a biaxial gyroscope LPR550. The data collected by the wireless inertial sensor nodes is transmitted to the PC via wireless receiving node. The central processing unit of the PC is Intel Pentium G2020 and random access memory is 4G. The system software is developed in Windows XP platform and written in C#. The software may configure a serial port and control sensors to collect data.

Four wireless inertial sensor nodes are attached to the right wrist, left wrist, waist, and right ankle of one player as shown in Fig. 1. Eighteen motions listed in Table I are performed by 12 badminton players. The sampling frequency is 100 Hz.

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The authors are with the School of Control Science and Engineering, Dalian University of Technology, Dalian 116024, China (e-mail: wangzl@dlut.edu.cn; guoming0537@126.com; zhaocong27@163.com).

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TABLE I
ACTIVITIES PERFORMED IN THIS PAPER

	Activity label	Activity description
Strokes	A1	Forehand serve
	A2	Backhand serve
	A3	Forehand clear
	A4	Backhand clear
	A5	Forehand rushing
	A6	Backhand rushing
	A7	Forehand chop
	A8	Backhand chop
	A9	Forehand lob
	A10	Backhand lob
	A11	Forehand push
	A12	Backhand push
	A13	Forehand hook on the corner
	A14	Backhand hook on the corner
Non-strokes motions	A15	Walking and pick up a ball
	A16	Ready gesture and shaking right wrist
	A17	Forehand cross footwork
	A18	Backhand cross footwork

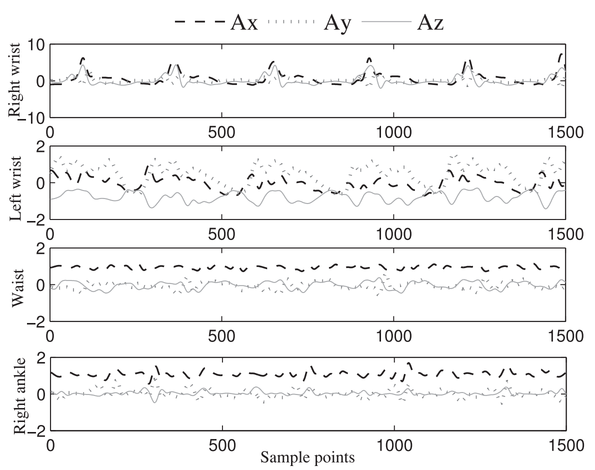

Fig. 2. Illustration of signal collected by four sensor nodes for forehand serve.

Fig. 2 shows an example of acceleration data for a forehand serve.

III. Badminton Stroke Recognition

The process of badminton stroke recognition (see Fig. 3) can be divided into five steps: noise reduction, badminton stroke detection, window segmentation, feature extraction and selection, and classification.

A. Noise Reduction

As motion signals collected by wireless inertial sensors contain some noise, and discrete wavelet transform is adopted to filter out noise signals in the paper. Motion signals can be decomposed into low-frequency approximation signals and high-frequency detail signals. Approximate signals contain the main characteristics of motion signals, and detail signals contain noise and disturbance signals. Therefore, we need to filter out the detail signals.

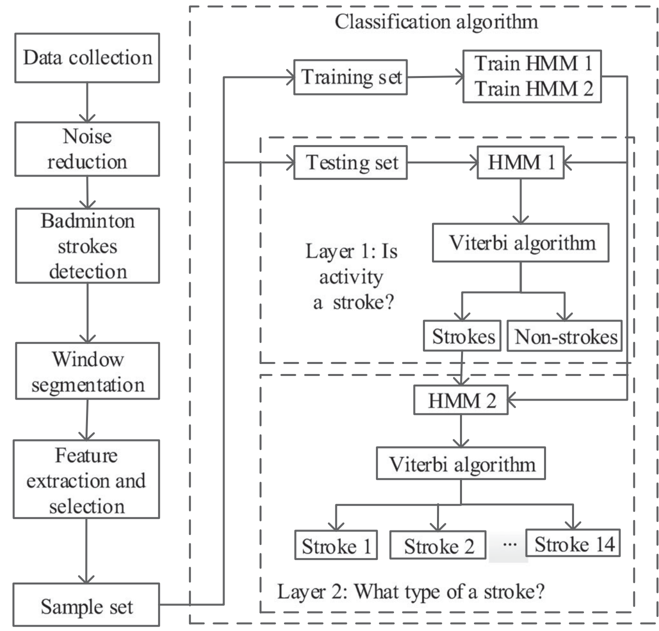

Fig. 3. Diagram of badminton stroke recognition.

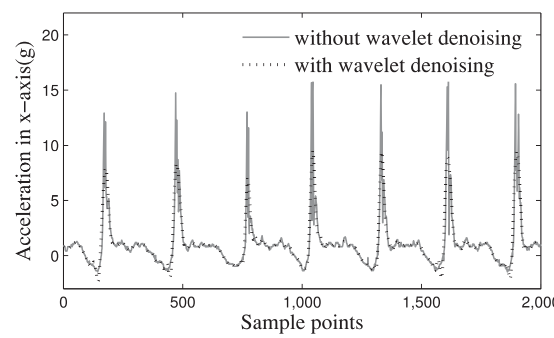

Fig. 4. Curves of acceleration data with and without wavelet denoising.

We mainly utilize wavelet function Coif5 [13] to filter out noise signals from acceleration signals and angular velocity signals in the paper. Fig. 4 shows the curves of acceleration data with and without wavelet denoising.

B. Badminton Stroke Detection

The inertial sensor node placed on the right wrist may detect a peak acceleration due to the impact of shuttle ball hitting the badminton racket. Detecting such data peaks provides the temporal location of badminton strokes (see Fig. 5).

We can detect badminton strokes by following two steps:

1) Compute resultant acceleration magnitude of every sampling point collected from the right wrist sensor node.
2) By the sliding window segmentation method, resultant acceleration signal is split into multiple windows with the fixed length ω_1, and there are 50% overlaps between each two adjacent windows. If the acceleration peak value in one window is larger than the threshold T, the point-in-time corresponding to the acceleration peak value is regarded as a candidate

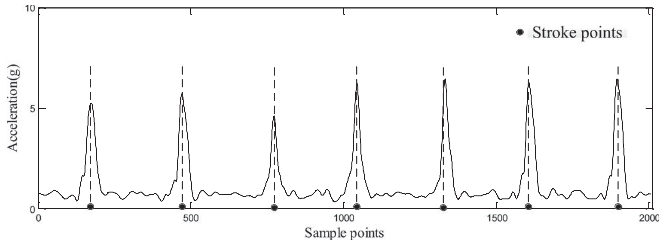

Fig. 5. Badminton stroke detection using acceleration magnitude of right wrist.

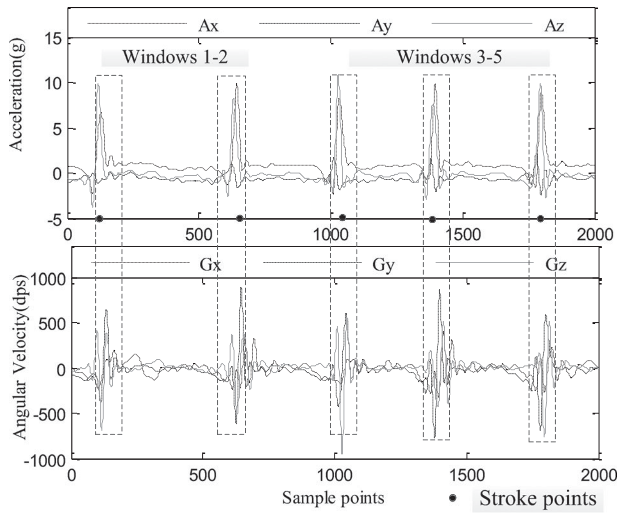

Fig. 6. Window segmentation of badminton motion data.

stroke point. If two adjacent stroke points t_1 and t_2 satisfy the formula $|t_1 - t_2| \leq \omega_2$, where ω_2 is the time threshold, then the stroke point corresponding to the smaller acceleration peak value is removed from candidate stroke points. Empirically, T is set at 1.5 g. The fixed length of sliding windows ω_1 is set at 2.5 s, which is determined according to the average cycle time of performed strokes. ω_2 is set at 1 s to filter out some false stroke points, because a window size of 1 s is deemed enough to describe motion information of a badminton stroke.

C. Window Segmentation

In the paper, a new window segmentation method named as window with containing stroke points (WCSP) is proposed. The window size of 1 s can avoid any additional motions performed before or after ball impact. When motion data are segmented by a sliding window, some stroke points may be located at the edge of the windows, such as windows 1 and 2 in Fig. 6. In order to describe all the strokes sufficiently, we need to remove any irrelevant information, and stroke points should be put at the center of windows, such as windows 3–5 in Fig. 6.

The window segmentation method (i.e., WCSP) is described as follows.

1) Determine badminton stroke points.

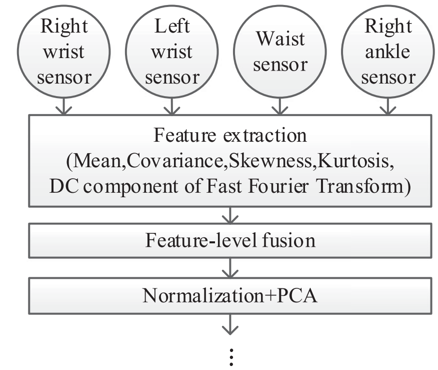

Fig. 7. Process of feature extraction and selection.

2) Select 50 sample points before and after one stroke point as the length of an observation window. Each window contains three-axis acceleration data and three-axis angular velocity data; therefore, each window contains 606 sample points. For example, for a stroke point t, we extract six-axis data in the time interval $[t - 0.5\text{ s}, t + 0.5\text{ s}]$ as the corresponding observation window, and it may make sure that the stroke point t can be located at the center of the observation window.

D. Feature Extraction and Selection

Both time-domain and frequency-domain features are extracted. The former include mean, covariance, skewness, and kurtosis, and the latter include dc component of fast Fourier transform (FFT)[14]. Here, mean can describe the speed of players' shot, covariance can describe the stability of the players' action, skewness can describe the instantaneous explosive force of players, and kurtosis and FFT can describe the situation of force and energy of motion signal, separately.

All features are extracted from both acceleration data and angular velocity data of each sensor node, and features of four sensor nodes are be fused to get the feature vectors, and the dimensionality of the feature vectors is 120.

Before feature selection, all features are normalized to $[0, 1]$. Then, we apply principal component analysis to reduce the dimensionality of normalized feature vectors. The threshold of the accumulative contribution rate is set at 99%. Fig. 7 shows the process of feature extraction and selection. For all experiments in Section II, the same feature set is used.

E. Classification

For the badminton training system, the classification algorithm we chose is the hidden Markov model (HMM) rather than the popular algorithm—support vector machine (SVM)[15]. First, the HMM can recognize the action sequence, which is suitable for this research. However, SVM cannot do this work. In addition, the computational complexity of the HMM is low, and it can do well when dealing with large dataset. However, for SVM, support vectors can be obtained based on the quadratic programming algorithm, which needs to cost much more computer resource in order to deal with large dataset.

Except for badminton strokes, there are some nonstroke motions such as walking and picking up a ball, etc. These nonstroke motions cannot be filtered out during the detection of badminton strokes because acceleration peaks of nonstroke motions are larger than 1.5 g. Therefore, we should filter out these nonstroke motions before starting stroke recognition by using the HMM.

A badminton stroke classification algorithm based on the two-layer HMM is proposed to recognize 14 types of badminton strokes in the paper. In the first layer, we use resultant acceleration magnitude of the right wrist sensor node to detect strokes and HMM-1 is utilized to recognize strokes and nonstroke motions. In the second layer, HMM-2 is applied to classify the strokes into 14 categories.

An HMM can be expressed by the following parameters: the number of states is N, and the individual states are described as $S = \{s_1, s_2 \ldots, s_N\}$, and the state at time t is q_t, then $q_t \in \{s_1, s_2 \ldots, s_N\}$. The number of distinct observation symbols is M, and the observation symbols are described as $V = \{v_1, v_2, \ldots, v_M\}$. The length of the observation sequence is T, and the observation sequence can be denoted as $O = \{o_1, o_2, \ldots, o_T\}$. The initial state probability distribution π, where

$$\pi = \{\pi_1, \pi_2, \ldots, \pi_N\},\ \pi_i = P(q_1 = S_i),\ 1 \le i \le N. \quad (1)$$

The state transition probability distribution $A = \{a_{ij}\}$, where

$$a_{ij} = P(q_{t+1} = S_j | q_t = s_i),\ 1 \le i, j \le N. \quad (2)$$

The observation probability distribution $B = \{b_{ij}\}$, where

$$b_{ij} = P(o_t = v_k | q_t = s_j),\ 1 < j < N,\ 1 \le k \le M. \quad (3)$$

For convenience, an HMM is defined as the triplet

$$\lambda = (\pi, A, B). \quad (4)$$

Because observations are continuous, a Gaussian mixture model (GMM) is used to describe the observation probability density function. The probability relation $b_j(o_t)$ between the hidden state s_j and the observation value o_t is represented by the following formula:

$$b_j(o_t) = \sum_{m=1}^{M_j} \omega_{j,m} b_{j,m}(o_t) = \sum_{m=1}^{M_j} N(o_t, \mu_{j,m}, \Sigma_{j,m}) \quad (5)$$

where M_j is the number of GMM component, $\omega_{j,m}$ is the mixture coefficient, $\mu_{j,m}$ is the mean vector, and $\Sigma_{j,m}$ is the covariance matrix.

Forward–backward algorithm, Viterbi algorithm, and Baum–Welch algorithm are adopted to train the HMM model. The training steps are listed as follows:

Step 1: Initialize HMM parameters $\lambda' = (\pi, A, B)$. Because π, A have little influence on the convergence of HMM parameters for training, they are initialized randomly or uniformly. While B has much more influence on the convergence of HMM parameters for training, it is initialized by Viterbi algorithm and k-means algorithm.

Step 2: The forward–backward algorithm is applied to calculate the likelihood probability $P(O|\lambda')$.

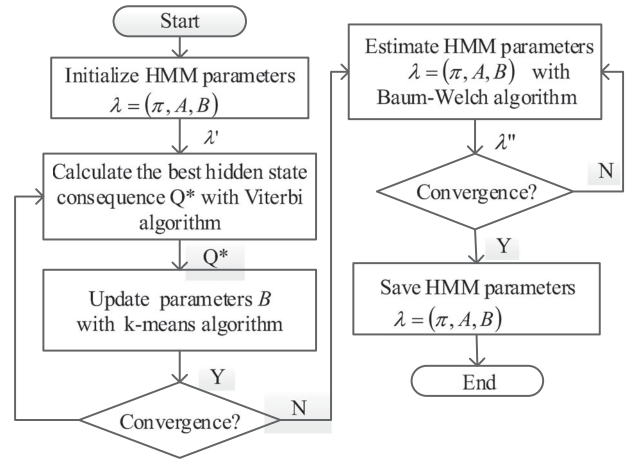

Fig. 8. Flow diagram of HMM parameter training.

Step 3: The Baum–Welch algorithm is utilized to reestimate the model to get new HMM parameters λ''.

Step 4: The forward–backward algorithm is used to calculate the likelihood probability $P(O|\lambda'')$ again.

Step 5: Repeatedly execute steps 3 and 4 until $P(O|\lambda'') - P(O|\lambda') < \varepsilon$, where ε is a given threshold value.

Step 6: After getting the final HMM parameters λ'', we adopt the Viterbi algorithm to find a set of hidden states that can maximize the likelihood probability $P(O|\lambda'')$. Here, each hidden state corresponds to one activity label.

Fig. 8 shows the flow diagram of HMM parameter training.

IV. Evaluation

A. Participants and Procedure

Twelve badminton players (eight males, four females) are recruited to collect the data. The ages of players range from 18 to 25 years. Six of them belong to our university badminton team, and the others belong to our university badminton club. All badminton players are right-handed.

Eighteen motions are performed (see Table I) by the players. Each person performs all motions 55 times in his or her own way. For the evaluation procedure, fourfold cross-validation strategy is used. First, the feature samples of 12 subjects are randomly divided into four equal pieces. Then, each time we choose three parts of them to be as the training data, and the only one left is as testing data. This process iterates for every part. The final result can be obtained by calculating the average recognition rate.

B. Filtering Nonstroke Motions

We need to filter out nonstroke motions before stroke recognition. We use the real dataset of 12 badminton players to set up two global feature vectors; one of them includes 14 types of badminton strokes, and the second global feature vector includes the four nonstroke motions as shown in Table I. HMM 1 is used to recognize badminton strokes and nonstroke motions. Here, the recognition results of badminton strokes and nonstroke motions are 99.27% and 99.19%, respectively.

TABLE II
RECOGNITION RESULTS OF THREE DIFFERENT WINDOW SEGMENTATION METHODS

Method	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Average
TSW	0.9963	0.999	0.9992	0.9911	0.7748	0.9584	0.7243	0.8768	0.8359	0.783	0.8727	0.9978	0.8462	0.7902	0.889
SWHA	0.999	0.9921	0.9991	0.9882	0.7795	0.9942	0.9619	0.9128	0.8781	0.7963	0.8801	0.9941	0.9605	0.8349	0.9265
WCSP	0.9982	0.9961	0.9962	0.9864	0.9921	0.998	0.996	0.9981	0.9958	0.9342	0.8956	0.9981	0.9943	0.9366	0.9796

TABLE III
RECOGNITION RESULTS OF DIFFERENT CLASSIFICATION ALGORITHMS

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Average
NB	0.9298	0.9388	0.9352	0.7662	0.613	0.8725	0.6975	0.7476	0.6396	0.4791	0.4866	0.785	0.7132	0.5371	0.7244
C4.5	0.9602	0.9573	0.9051	0.8948	0.7174	0.8737	0.6832	0.8049	0.7197	0.7314	0.5914	0.8708	0.6393	0.6321	0.7844
LDF	0.9641	0.9881	0.9874	0.8756	0.8075	0.8753	0.7371	0.8085	0.7227	0.7054	0.6911	0.8239	0.7502	0.7562	0.8209
SVM	0.9772	0.9981	0.9982	0.9875	0.9849	0.9992	0.9551	0.9588	0.9558	0.9515	0.9279	0.9965	0.9406	0.947	0.9698
Our Method	0.9982	0.9961	0.9962	0.9864	0.9921	0.998	0.996	0.9981	0.9958	0.9342	0.8956	0.9981	0.9943	0.9366	0.9796

TABLE IV
AVERAGE RECOGNITION ACCURACY AND TIME OF DIFFERENT CLASSIFICATION ALGORITHMS

	NB	C4.5	LDF	SVM	Our Method
Accuracy(%)	72.44	78.44	82.09	96.98	97.96
Time(s)	2.5	16.1	6.1	7452.6	19.5

C. Comparison of Different Window Segmentation Methods

In order to verify the effectiveness of the window segmentation method (i.e., WCSP), two different window segmentation methods called traditional sliding window (TSW) and sliding window with high acceleration (SWHA) are used to compare with WCSP.

TSW: The window length is 1 s, each window contains 600 sample points, and every two adjacent windows have no overlapping data.

SWHA: The window length is same as that of TSW. The difference is, in SWHA, those windows whose acceleration peak values are larger than 1.5 g are preserved [9].

Table II shows the recognition results of the three different window segmentation methods. It is shown that the window segmentation method proposed in this paper achieves the highest recognition accuracy, and it is superior to the other two window segmentation methods. Furthermore, compared with the other two methods, the proposed window segmentation method may describe movement characteristics of strokes, filter out the windows that are irrelevant to strokes, and cost less time to create and train the model.

D. Comparison of Multiple Classification Algorithms

Naive Bayes (NB) [16], C4.5 decision tree [17], SVM, linear discriminant function (LDF) [18], and two-layer HMM are used to recognize 14 types of strokes, respectively. Recognition results are shown in Tables III and IV. The recognition time in Table IV is the computational time of each classifier, and it can reflect the computational cost clearly. Tables III and IV show that the average recognition accuracy of two-layer HMM is 97.96%, which is better than that of other four classification algorithms. Although the average recognition accuracy of SVM may reach 96.98% that is only 0.98% less than our method, its recognition time is 7542.6 s, which is much longer than ours. The recognition time of NB, C4.5, and LDF are shorter than our method, but the recognition accuracies of NB, C4.5, and LDF are much worse than the method proposed in this paper. Therefore, the two-layer HMM classification algorithm proposed in this paper achieves the best performance in terms of recognition accuracy and recognition time.

E. Recognition Performance With All the Possible Sensor Combinations

We apply four sensors to recognize 14 types of badminton strokes. However, too many sensor nodes placed on the human body may make the players feel uncomfortable. Therefore, on the premise of guaranteeing the recognition accuracy of different badminton strokes, sensor nodes are used as few as possible. Suitable locations for these wearable sensor nodes are investigated. From Fig. 1, it can be seen that four wireless inertial sensor nodes are attached to the right wrist, left wrist, waist, and right ankle, respectively. We also conduct a variety of possible combinations for the locations of four sensor nodes. Table V shows the recognition results.

The recognition accuracy of right wrist sensor node is the highest if we use only one sensor node, but the average recognition accuracy is just 81.63%, which shows that the recognition performance is relatively low, if we use only one sensor node. If two sensor nodes are used to recognize different badminton strokes, it can be seen that the recognition accuracy obtained by using both right wrist sensor node and right ankle sensor node is high to 91.21%. Compared with the case of using all sensor nodes, it is not wide in the gap. Therefore, it is concluded that using right wrist sensor node and right ankle sensor node may also obtain better recognition performance, and it illustrates that the right wrist and the right ankle are the most suitable body

TABLE V
RESULT BY FUSING SENSOR NODE ALGORITHMS

sensor unites	Activity label														Average
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	
only 1	0.99	0.9966	0.8998	0.8948	0.9941	0.6419	0.7977	0.8415	0.691	0.515	0.7628	0.7432	0.9707	0.6861	0.8163
only 2	0.5321	0.9051	0.5177	0.2968	0.2066	0.5339	0.0825	0.1344	0.169	0.1748	0.2502	0.5037	0.1223	0.1371	0.3262
only 3	0.6514	0.8992	0.6281	0.6237	0.1225	0.457	0.4854	0.2329	0.2532	0.2724	0.2412	0.7409	0.0905	0.268	0.4262
only 4	0.8285	0.8683	0.5764	0.6995	0.2364	0.8092	0.2693	0.3988	0.3706	0.3576	0.2241	0.5736	0.4059	0.4243	0.503
fusion(1+2)	0.9959	0.9942	0.9908	0.9124	0.9853	0.5028	0.9078	0.8564	0.8121	0.6702	0.7497	0.7379	0.9576	0.7164	0.8432
fusion(1+3)	0.9888	0.9936	0.9429	0.9172	0.9232	0.7955	0.8897	0.8966	0.8021	0.7565	0.7736	0.9471	0.9725	0.8491	0.8897
fusion(1+4)	0.9597	0.9967	0.9992	0.916	0.9887	0.9734	0.9022	0.8878	0.8589	0.7287	0.8401	0.9671	0.9661	0.7496	0.9121
fusion(2+3)	0.9597	0.9967	0.8677	0.8946	0.5202	0.4396	0.5495	0.6612	0.6088	0.6874	0.5799	0.9362	0.7422	0.6103	0.7183
fusion(2+4)	0.9537	0.9983	0.8531	0.8303	0.5326	0.5976	0.5342	0.698	0.5872	0.6973	0.6112	0.822	0.7651	0.6151	0.7254
fusion(3+4)	0.9113	0.9805	0.7705	0.8092	0.4462	0.9975	0.5494	0.7001	0.3722	0.4753	0.5866	0.6672	0.4788	0.5862	0.6665
fusion(1+2+3)	0.994	0.9966	0.9982	0.9172	0.9959	0.8951	0.9798	0.9587	0.9501	0.9584	0.8841	0.949	0.9822	0.9348	0.9571
fusion(1+2+4)	0.998	0.9965	0.9947	0.9204	0.9941	0.8926	0.9962	0.9929	0.9913	0.9256	0.8994	0.9816	0.9766	0.8622	0.9605
fusion(1+3+4)	0.9908	0.9921	0.9911	0.9319	0.9981	0.9978	0.9964	0.9924	0.9697	0.821	0.8789	0.9978	0.9961	0.8622	0.9597
fusion(2+3+4)	0.9838	0.9925	0.9201	0.9349	0.6235	0.9402	0.5452	0.7914	0.5645	0.7567	0.6367	0.755	0.5477	0.6485	0.7606
fusion(1+2+3+4)	0.9982	0.9961	0.9962	0.9864	0.9921	0.998	0.996	0.9981	0.9958	0.9342	0.8956	0.9981	0.9943	0.9366	0.9796

Note: 1-right wrist, 2-left wrist, 3-waist, 4-right ankle.

parts to wear sensor nodes for recognizing different badminton strokes. On the other hand, Table V shows that for all kinds of combinations of the four sensor nodes, we can get ideal results if a sensor node attaching to the right wrist is in the combinations, which shows that the sensor node attached to the right wrist plays a dominant role among the four sensor nodes. It can also be verified by motion data that badminton players use their right wrists to control their rackets and perform different strokes in the experiment.

V. CONCLUSION

Badminton stroke recognition based on BSN is studied in this paper. Conclusions are drawn as follows.

1) Aiming at the lack of inertial dataset for badminton strokes, a dataset which contains 12 badminton players and 18 badminton motions, is established. This dataset can be used as baseline data for badminton sport research.
2) Aiming at the characteristics of badminton strokes, a window segmentation method based on stroke detection is proposed. The method can detect strokes and realize that each window contains the motion data of one stroke with the most stroke information and the least interference information. Compared with the other two window segmentation methods, our method achieves the best recognition accuracy.
3) A two-layer HMM classification algorithm is proposed to recognize 14 types of badminton strokes. Experimental results show that the two-layer HMM classification algorithm achieves the best performance in terms of recognition accuracy and recognition time.
4) Suitable locations of these wearable sensor nodes have been investigated. Motion data collected from right wrist sensor node, left wrist sensor node, waist sensor node, and right ankle sensor node are used for badminton stroke recognition, respectively; we conduct a variety of possible combinations for the locations of four sensor nodes. The result shows that the right wrist and the right ankle are the most suitable body parts to wear sensor nodes for recognizing different badminton strokes.

In the future, we plan to apply the system in a realistic training environment or a real game. For this purpose, we need constantly improve the performance of the system that may conduct real-time monitoring, and the performance of the algorithm needs to be further improved and reduce the response time. Besides, the comfortableness of wearing the sensor nodes for the badminton players needs to be taken into consideration.

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