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Integrated Sensing and Computing for Wearable Human Activity Recognition with MEMS IMU and BLE Network

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Abstract: The miniature sensor devices and power-efficient Body Area Networks (BANs) for Human Activity Recognition (HAR) have gained increasing interest in different fields, including Daily Life Assistants (DLAs), medical treatment, sports analysis, etc. The HAR systems normally collect data with wearable sensors and implement the computational tasks with a host machine, where real-time transmission and processing of sensor data raise a challenge for both the network and the host machine. This investigation focuses on the hardware/software co-design for optimized sensing and computing of wearable HAR sensor networks. The contributions include (1) design of a miniature wearable sensor node integrating a Micro-Electro-Mechanical System Inertial Measurement Unit (MEMS IMU) with a Bluetooth Low Energy (BLE) in-built Micro-Control Unit (MCU) for unobtrusive wearable sensing; (2) task-centric optimization of the computation by shifting data pre-processing and feature extraction to sensor nodes for in-situ computing, which reduces data transmission and relieves the load of the host machine; (3) optimization and evaluation of classification algorithms Particle Swarm Optimization-based Support Vector Machine (PSO-SVM) and Cross Validation-based K-Nearest Neighbors (CV-KNN) for HAR with the presented techniques. Finally, experimental studies were conducted with two sensor nodes worn on the wrist and elbow to verify the effectiveness of the recognition of 10 virtual handwriting activities, where 10 recruited participants each repeated an activity 5 times. The results demonstrate that the proposed system can implement HAR tasks effectively with an accuracy of 99.20 %.

Keywords: Integrated sensing and computing, Human Activity Recognition (HAR), Body Area Networks (BANs), Micro-Electro-Mechanical System Inertial Measurement Unit (MEMS IMU), Bluetooth Low Energy (BLE).

1. INTRODUCTION

With the continuous progress of novel sensing and computing techniques, Human Activity Recognition (HAR) has attracted extensive attention and become a promising approach for applications in medical treatment, body kinematics, Human-Computer Interaction (HCI), Virtual Reality (VR), motion analysis, Daily Living Assistant (DLA) and elderly care [1]-[4]. Compared with Computer Vision (CV)-based techniques, the wearable sensing device-based solution breaks the limits of space by getting rid of the fixed and bulky equipment. It is not only free from privacy leaks but also convenient to use in people's daily life. It is undeniable that a wearable sensing network has become a competitive solution for various HAR applications [5].

In recent years, many novel wearable HAR techniques and systems have been reported in the literature [6]. These HAR systems mainly improve the performance of the system by introducing new sensing techniques and mounting sensors on new body part locations [7] or combining with wireless communication technologies, such as WIFI, Bluetooth [8], Radio Frequency Identification (RFID), and ZigBee [9], [10]. Wearable HAR systems can be divided into two categories: single-sensor systems and multi-sensor systems.

There are many single-sensor HAR-related studies for different applications [11], [12], such as household appliance control [13], exercise data recording [14], and daily activity recognition [15], [16]. Irene et al. [17] developed a low-cost wearable sensor node with a triaxial accelerometer that could transmit data to a PC via ZigBee and recognize simple daily life motions based on leg kinematics, including sitting, standing, and walking. Yen et al. [18] proposed a waist wearable device for daily activity analysis of patients with diseases like dialysis patients who have blood vessel prostheses on their arms, which make them inconvenient for strenuous exercises. However, the data collected by a single sensor may contain fewer features, which may be inadequate for accurate classification. Therefore, many investigations tend to integrate more sensors and deal with the multi-channel data sources with data fusion algorithms using more powerful computing devices. Santoyo-Ramón et al. [19] designed a wearable fall detection system based on Body Area Network (BAN) with four sensor nodes to transmit data to a smartphone via Bluetooth for data processing. Li et al. [20] proposed Wi-Motion, a WIFI signal-based human activity recognition system. The Wi-Motion introduced the amplitude and phase information extracted from the Channel State

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Information (CSI) sequence and eventually obtained an average accuracy of 96.6% for the recognition of 5 typical human activities in a Line-of-Sight (LoS) environment. A Multi-sensor system usually improves the recognition accuracy at the cost of increasing the computational complexity [21]. Reducing the computational complexity has been a common challenge for multi-sensor HAR systems.

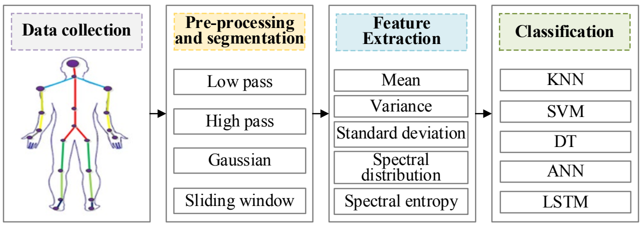


Fig.1. Diagram of algorithmic flow for HAR.

The optimization of data processing and decision-making algorithms has been considered an effective way of improving the performance of HAR. As shown in Fig.1., HAR functions mainly include four steps: data collection, data segmentation, feature extraction, and classification. The improvement towards an optimized HAR algorithm mainly focuses on the steps of feature extraction and classification.

Hsu et al. [22] utilized the nonparametric weighted feature extraction algorithm and the Principal Component Analysis (PCA) to reduce the dimensions of features, which can achieve a recognition accuracy of 98.23 % for 10 common domestic activities. Tian et al. [23] used a hybrid feature selection method based on Game Theory-based Feature Selection (GTFS) and Binary Firefly Algorithm (BFA) to optimize the feature set and classification parameters and used the kernel extreme learning machine as the classifier, which resulted in a robust system. Hassan et al. [24] proposed a smartphone inertial sensors-based HAR system, which used Kernel Principal Component Analysis (KPCA) and Linear Discriminant Analysis (LDA) for further processing of the features, and used Deep Belief Networks (DBN) to train the features for recognition. The performance is better than normal Artificial Neural Networks (ANNs). In addition, there are many related investigations of algorithm optimization for HAR [25]-[29]. Although the algorithm optimization can improve the accuracy of HAR, it may increase the computational complexity which eventually introduces a heavier load for the host machines.

Wearable HARs have made significant progress in both sensing devices and algorithms, but they still face technical challenges. Firstly, the sensor nodes are usually bulky for wearable applications, which may affect people's daily activities; Secondly, the sensor nodes normally send raw data to a host PC for further processing, which requires high throughput of wireless communication; Thirdly, the data fusion, feature extraction, and classification algorithms may introduce computational load to the host PC and jeopardize its real-time performance. Therefore, the investigations of optimized sensing and computing of wearable systems for unobtrusive activity recognition become the trend of HAR.

Motivated by the above technical challenges, the work of this investigation focuses on the following technical issues: Firstly, a technical solution for miniaturized wireless sensor nodes by integrating MEMS IMU and Bluetooth Low Energy (BLE) to constitute a BAN system for unobtrusive HAR; Secondly, the optimization of the computational resources by allocating in-situ pre-processing and feature extraction to the sensor nodes, which relieves the burden of both the data transmission of BAN and the computation of host PC; Thirdly, the investigation of Particle Swarm Optimization-based Support Vector Machine (PSO-SVM) and Cross Validation-based K-Nearest Neighbors (CV-KNN) for the classification of human activities.

The rest of this article is structured as follows: Section II presents the design of the proposed wearable HAR system including the hardware module design and computational resource allocation; Section III describes the proposed data processing algorithm for HAR; Section IV gives the experimental studies to verify the proposed solutions, and the conclusion is drawn in Section V.

2. SYSTEM DESIGN: SENSOR NODES AND WIRELESS BAN

The schematic of the wearable BAN for HAR is shown in Fig.2. Multiple wearable sensor nodes constitute the BAN for data collection via BLE, and the data is transmitted to a host PC for further processing and classification. This section describes the design of the proposed sensor nodes and the corresponding computational resource optimization.

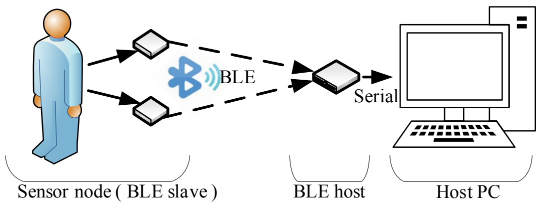
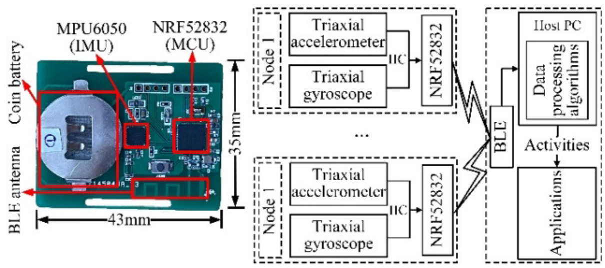


Fig.2. Schematic of BLE-based BAN for HAR.

A. *Hardware design of the sensor nodes*

The proposed sensor nodes consist of a MEMS IMU MPU6050, a BLE in-built MCU NRF52832, and a coin battery. As shown in Fig.3., the main controller NRF52832 is a System-on-Chip (SoC) device with a 64 MHz Cortex-M4 core and an in-built BLE module sized 6.0×6.0 mm. The MPU6050 is a MEMS IMU which outputs triaxial acceleration and triaxial angular rate sized 4.0×4.0 mm. The MCU implements the data collection and pre-processing, and transmits the processed data to the host PC via BLE. The components are assembled on an FR4 substrate with a thickness of 0.8 mm and a size of 4.3×3.5 cm.



a) Sensor node hardware b) Wearable nodes with BLE

Fig.3. Wearable sensor nodes with BLE.

B. Optimization of computational resource

Since the transmission of raw sensor data to the host PC may introduce a load for both the communication network and the host PC, it is a promising way to allocate part of the computational tasks to the sensor nodes. Normally, the computation can be separated into three steps: pre-processing, feature extraction and processing, and decision making for classification. Since the former two steps both handle the raw sensor data, they are usually time-consuming. It also takes time to transmit the raw data to a host PC. However, the decision-making dealing with the limited number of features may be a lightweight computation.

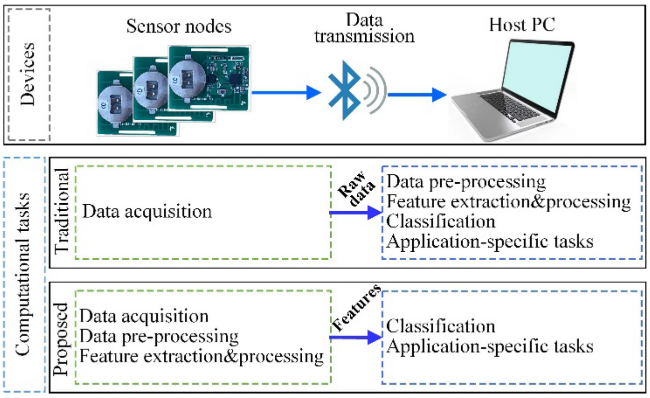


Fig.4. Optimization of computational resources.

As shown in Fig.4., this investigation introduces an integrated sensing and computing technique, which allocates the computation tasks of pre-processing and feature extraction to the sensor nodes. Then, the limited data of features can be transmitted to the host PC via BLE for classification and application-specific tasks. By taking advantage of the limited computational resources of MCU, the time-consuming data transmission can be eliminated and the computation load of the host PC can be alleviated by distributing the computational tasks to the sensor nodes.

3. DATA PROCESSING ALGORITHMS FOR WEARABLE HAR

The raw data obtained from the MEMS IMU are triaxial acceleration and triaxial angular rate. To make use of the data streaming for activity recognition, the algorithm flow shown in Fig.5. is proposed.

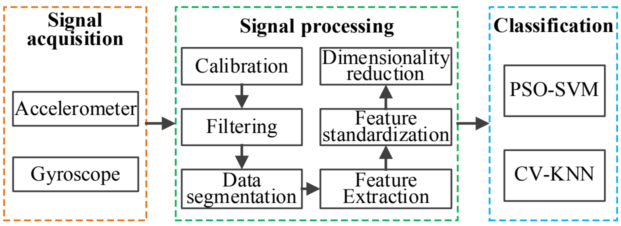


Fig.5. The data processing flowchart for HAR.

The sensor data acquisition is executed with a sampling rate of 100 Hz, followed by data filtering, data segmentation, feature extraction, feature data standardization, and feature dimensionality reduction. The final step is a feature-based classification for the decision-making of activity recognition.

A. Data pre-processing

A.1. Sensor calibration

For MEMS IMUs, bias error and random noise are the main factors that are harmful to the performance of HAR. Therefore, the correction of bias and cancellation of random error is conducted in the preprocessing. The models of bias and random error for the triaxial acceleration and triaxial angular rate can be described as follows[30]:

$$a_r(i) = f(a(i), g) + a_b(i) + n_a \tag{1}$$

$$\omega_r(i) = \omega(i) + \omega_b(i) + n_w \tag{2}$$

where $a_r(i)$ and $\omega_r(i)$ are the accelerometer and gyroscope measurements, $a(i)$ and $\omega(i)$ are the ideal measurements without errors, $a_b(i)$ and $\omega_b(i)$ are the biases, n_a and n_w are the random noises. In equation (1), $f(a(i),g)$ denotes the force the accelerometer measures, where g is the gravitational acceleration. For HAR applications, denoising is not a key factor determining the performance. Therefore, lightweight denoising algorithms are expected to decrease the computational load. In this investigation, a static calibration is employed to deal with the bias. The sensor is put in a static state to collect 500 samples of triaxial acceleration and triaxial angular rate for the calibration of bias. To suppress the impact of random error, a moving average filter is employed for each data sample.

A.2. Moving average filter for noise cancellation

To reduce the influence of random noise in the sensor data acquisition, the moving average filter is employed to improve the quality of data. The calculation of the moving average filter is:

$$X(n) = \frac{x(n) + x(n+1) + \cdots + x(n+N-1)}{N} \tag{3}$$

The selection of N is a critical issue, as a too-large N will cause data distortion and jeopardize the features of the data, and a too-small N may not be able to effectively remove the noise. Through repeated experimental verifications, the selected window size N is set to 5.

A.3. Data segmentation

Since the input data for human activity recognition is a continuous time-series signal, an appropriate length of the sliding window should be selected for further feature extraction and classification.

The selection of the window size is also critical for further data processing. When the window size is too small, it can hardly incorporate enough information to recognize the activities. When the window size is too large, it may cause serious delays that are unacceptable for the real-time requirements of HAR applications. In this investigation, a sliding window with a length of 100 sampling points and 50 % overlap is selected to segment the continuous signal.

B. Feature extraction and dimensionality reduction

B.1. Feature extraction

The process of feature extraction should be able to retain the critical information that is contained in the data for HAR. The mainstream feature extraction methods for HAR may include time domain, frequency domain, and time-frequency domain methods. This investigation mainly uses the methods of time-domain feature extraction. For each dimension of data, 8 selected features including mean, standard deviation, maximum, minimum, range, kurtosis, skewness, and quartile are extracted for further processing. The dimension of the feature matrix is 96, which is the product of data channel 12 and the quantity of features 8.

B.2. Feature data standardization

For the convenience of the following calculations, the scale of each feature in the feature vectors should be regulated within the same range. The processing of the feature vector in this step is named feature data standardization. Suppose the matrix of the feature vector is $S_{n\times m}$ where there are n channels and each has m features, the standardization is implemented with formula (4) to convert the elements in the range [0,1].

$$s_{ij}^{*} = \frac{s_{ij} - \overline{s}_j}{\sqrt{\operatorname{var}\left(s_j\right)}} \tag{4}$$

where standardized element s_{ij}^{*} is obtained by the original element s_{ij}, the average of the j^{th} column, and the Root Mean Square (RMS) of j^{th} column. The average and RMS of j^{th} column can be obtained with (5) and (6).

$$\overline{s}_j = \frac{1}{n}\sum_{i=1}^{n} s_{ij} \tag{5}$$

$$\operatorname{var}\left(s_j\right) = \frac{1}{n-1}\sum_{i=1}^{n}\left(s_{ij} - \overline{s}_j\right)^2 \tag{6}$$

B.3. PCA-based feature dimensionality reduction

The compression of feature dimension is another step before classification, which reduces the dimensionality of the high-dimension feature matrix and simplifies the calculation. In this investigation, the PCA is employed to reduce the standardized m-dimensional matrix to the p-dimensional using a transformation matrix. The purpose of PCA-based feature dimensionality reduction is to obtain the independently correlated data features to be used for classification.

Table 1. Accuracy of KNN with different quantities of principal components.

Algorithm	Qty of principal components	Accuracy (%)
KNN	15	89.77
KNN	18	92.05
KNN	20	91.48

For the PCA-based dimensionality reduction in this investigation, the cumulative contribution of the principal components is shown in Fig.6. When the quantity of principal components is 18, the cumulative contribution reaches 92.03 %, which is acceptable for further classification.

Table 1. gives the relationship between the number of principal components and the accuracy of recognition for the KNN algorithm. When the quantity of principal components is 18, the accuracy of recognition reaches 92.05 %. In this investigation, the feature dimensionality of the feature set is reduced from 96 to 18.

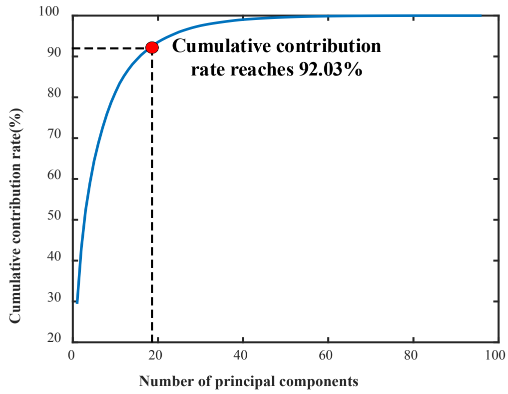


Fig.6. Feature matrix dimensionality reduction.

C. Classification algorithms

The classification algorithms play an important role in the performance of HAR. The commonly used classification methods for HAR include decision tree, KNN, SVM, naive Bayes, etc. Among the methods, KNN is considered a simple and effective one, and SVM is considered a mature and efficient choice. The work of this investigation is based on SVM and KNN.

C.1. Parameter optimization-based SVM

As an efficient supervised learning algorithm, SVM is a binary classification model which defines a linear classifier with the largest interval in space. The basic idea of SVM is to classify linearly separable data through the optimal hyperplane and to maximize the geometric distance from the sample data on both sides of the hyperplane.

For the optimization of SVM, the kernel function parameters ξ_i and penalty factor C are the key parameters to determine its performance. In this investigation, the Cross-Validation (CV) method and the PSO algorithm are used to automatically select the optimal ξ_i and C to obtain the SVM classification model with the best performance.

In the CV method, the parameters ξ_i and C are combined with a fixed step size within a certain value range. The training set data under different combinations of ξ_i and C are divided into K groups. Each group of data is used as a test set, and the remaining K-1 groups of data are used as training sets. The average classification accuracy of the final test set for each combination is taken as the accuracy of this group of models. Then, compare the accuracy rate of the model under different combinations of ξ_i and C, where the highest accuracy rate corresponds to the optimal ξ_i and C.

The principles of PSO-SVM algorithm can be described as follows [31]. Suppose there is a swarm, of size n, each particle $P(i)$ (i=1, 2, …, n) in the swarm is characterized by three parameters: (1) its current position $p(i)$, which refers to a candidate solution of the optimization problem at an iteration; (2) its velocity $v(i)$ and (3) the best position $p_b(i)$ identified during is past trajectory. Let $p_g(i)$ be the best global position identified by overall trajectories traveled by the particles of the swarm, the optimal position is obtained by one or more fitness functions. The particles moving in the searching process can be calculated with the following equations:

$$\begin{aligned} v(\mathrm{i}+1) &= wv(i) + c_1 r_1(i)[P_b(i) - p(i)] \\ &\quad + c_2 r_2(i)[P_g(i) - p(i)] \end{aligned} \tag{7}$$

$$p(i+1) = p(i) + v(i+1) \tag{8}$$

where $r_1(i)$ and $r_2(i)$ are random variables from a uniform distribution in the range [0,1], w is the inertia weight, and c_1 and c_2 are learning factors. Equation (7) is used to compute the velocity of particles in the swarm, and equation (8) is used to update the position of particles. Both equations (7) and (8) are iterated until the search process reaches a convergence criterion.

To carry out the classification of k human daily activities, a one-to-one multi-class strategy based on the combination of multiple SVM is selected, where the quantity of classifiers is $k(k+1)/2$. When the sample to be tested is input for classification, the outputs of the classifiers are counted and the category with the most votes is the activity class of the input sample. In this investigation, the outputs of the classifiers are the 10 pre-defined activity labels.

C.2. CV-KNN

Compared to SVM, KNN is a lazy learning algorithm that does not need a model training process. The samples to be tested are processed directly according to the principles of the KNN algorithm.

The construction of the KNN algorithm classification model includes three critical elements: distance measurement, finding the K value, and decision making. This investigation uses the Euclidean distance metric. Suppose there are two n dimension vectors x = (x1, x2, x3, … xn) and y = (y1, y2, y3, … yn). The Euclidean distance can be calculated as follows:

$$D(x, y) = \sqrt{\sum_{i=1}^{n} \left(x_i - y_i\right)^2} \tag{9}$$

For finding the K values, this investigation employs the K-fold cross-validation. For decision making, the class of a sample is determined by the class of its K nearest neighbors.

4. EXPERIMENTAL STUDIES

To evaluate the proposed methods, the experimental studies are conducted with participants wearing the sensor nodes to repeat pre-defined activities. The activities chosen for the evaluation are the virtual writing of numbers 0-9 with the right hand in the air.

A. Experimental Setup and Data Preparation

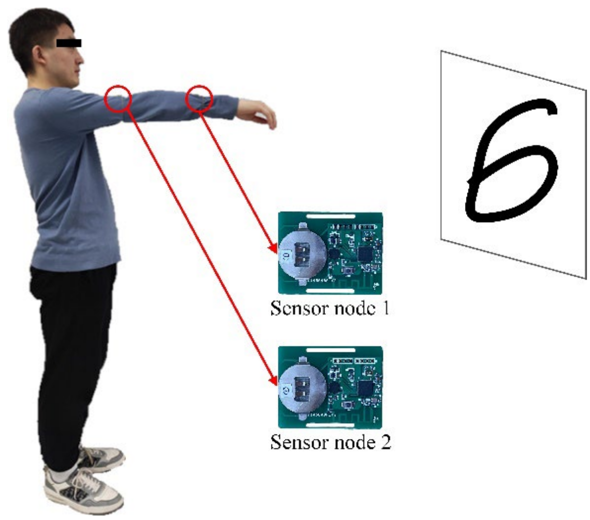


Fig.7. Experimental setup.

In the experiment, 10 participants are recruited to perform the activities to evaluate the proposed system and methods. For the 10 participants, there are 5 males and 5 females, whose heights are 170±10 cm, weights are 60±10 kg, and ages are 23-26 years old.

As shown in Fig.7., the sensor nodes are mounted on the wrist and elbow of a participant. Each participant is requested to remain still for 2 seconds before starting and after finishing an activity. At the beginning of an activity, a participant is requested to stand straight with his/her left arm hanging down naturally and his/her right arm hanging flat. After standing still for about 2 seconds, the participant is requested to start to perform a virtual writing activity. After that, the participant needs to stand still for 2 seconds before completing the data collection. Each participant repeats the handwriting activities of numbers 0-9 for 5 times. The quantity of data generated in the experiment is 500 samples.

In the experiment, the sampling rate is 100 Hz and each sample contains data on the triaxial acceleration and triaxial angular rate. The pre-processing, feature extraction and standardization are completed with the MCU of the sensor nodes. The host PC then receives the feature data for classification via the BLE network. The host PC for the tests is Lenovo 80S1 with a quad-core CPU at 2.5GHz, 8GB RAM, and the software platform is MATLAB2020b in Windows 10 environment.

B. Data preparation

The multiple sensor nodes in a BAN work in an asynchronous way. They have their timing for data acquisition, preprocessing, feature extraction, and data transmission. The data from different nodes are integrated with the host PC. Since the preprocessing and feature extraction can be done in the sensor nodes, both the rate and the amount of data to transmit are largely decreased. Therefore, the delay in the sensor node can be neglected and the data from the multiple nodes can be combined into channel arrays with the host clock. The integrated data can be used for decision-making.

The data sets that consist of the sensor data and their corresponding activity category tags are divided into two categories: the training set and the test set, which occupy 60 % and 40 %, respectively. There are differences in the different activities and the same activity for different people. To reduce this influence and obtain a more practical and effective model, the proportion of the training data for each activity in the data set is the same. Considering the differences in activities between participants, the percentage of samples for a certain participant in the training set and test set are identical. With the preprocessing, data segmentation, and feature extraction in Section 3, parameter-optimized SVM and KNN algorithms are expected for the classification of different activities. The kernel function parameters ξ_i and penalty factor C are the key parameters to determine. Once the key parameters are determined, the test set is then input to the classifiers and the prediction results of the activity classification are obtained.

C. Performance evaluation

The purpose of the evaluation is to assess the performance of CV-KNN, CV-SVM, and PSO-SVM for HAR. The key indicators to evaluate the classifiers are accuracy (Acc), precision (P), and recall (R), which are calculated as follows:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \qquad (\ )$$

$$P = \frac{TP}{TP+FP} \qquad (\ )$$

$$R = \frac{TP}{TP+FN} \qquad (\ )$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

C.1. Evaluation of the classifiers

The confusion matrix and parameters of accuracy, precision, and recall are provided to evaluate the classifiers. The Acc, P, and R of the CV-KNN are given in Table 2., and that of CV-SVM and POS-SVM are given in Table 3.

Table 2. Evaluation of CV-KNN classifiers.

Methods	Acc (%)	P (%)	R (%)
3-fold KNN	92.05	92.26	95.13
5-fold KNN	89.77	90.38	93.05
10-fold KNN	94.89	95.20	95.81

Table 3. Evaluation of CV-SVM and PSO-SVM classifiers.

Methods	Acc (%)	P (%)	R (%)
3-fold SVM	98.86	98.79	98.70
5-fold SVM	98.86	98.79	98.70
10-fold SVM	98.86	98.79	98.70
PSO-SVM	99.20	99.41	99.47

Table 2. gives the accuracy, precision, and recall of the 3-fold, 5-fold, and 10-fold CV-KNN classifiers. It is clear that the 10-fold CV-KNN outperforms its peers in all the parameters. Table 3. gives the parameters of the 3-fold SVM, 5-fold SVM, 10-fold SVM, and PSO-SVM. The accuracy, precision, and recall of the PSO-SVM are 99.20 %, 99.41 %, and 99.47 %, which outperforms the other three SVM and the CV-KNN classifiers. Among all the classifiers for the evaluation, PSO-SVM has been the most competitive choice.

C.2. Confusion matrix of different classifiers

The confusion matrixes of the CV-KNN and CV-SVM classifiers are shown in Fig.8. The parameter optimization-based SVM algorithms give fewer prediction errors than the CV-KNN algorithms. Among them, the PSO-SVM shows the best performance in the confusion matrix.

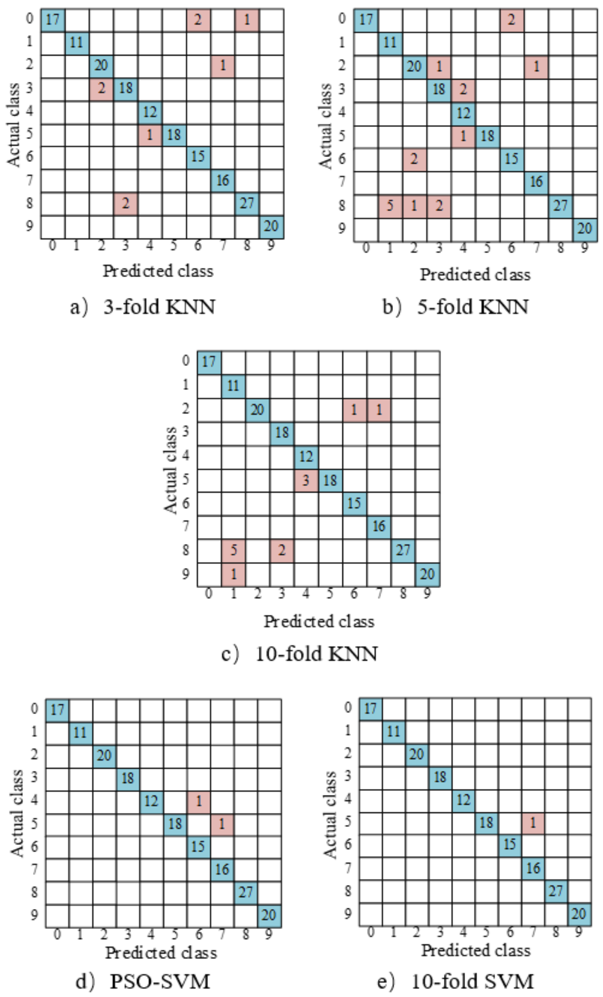


Fig.8. Confusion matrix of KNN and SVM

D. Results and evaluation

D.1. Classification performance for HAR

The accuracy and algorithm operation time are obtained to evaluate the performance of classifiers for HAR, which are given in Table 4.

From the results, the activity recognition accuracy of PSO-SVM is 99.20 %, which is better than CV-SVM at 98.86 % and CV-KNN at 94.89 %. The operation time of PSO-SVM for decision-making is 9.23 ms, which also outperforms the other two counterparts.

Table 4. Comparision of different classification algorithms in accuracy and operation time

Algorithms	Accuracy (%)	Operation Time (ms)
CV-KNN	94.89±0.00	14.93±2.44
CV-SVM	98.86±0.00	11.85±1.31
PSO-SVM	99.20±0.55	9.23±0.74

D.2. Evaluation of single- and dual-sensor nodes network

To evaluate the contribution of the triaxial accelerometer and triaxial gyroscope and demonstrate the superiority of the multiple nodes system. The performance of the HAR system with accelerometer, gyroscope, and both accelerometer and gyroscope are given in Table 5.

Table 5. Accuracy and operation time of HAR systems with different sensor signals.

Sensors	Accuracy (%)	Operation Time (ms)
Accelerometer	85.00±1.08	9.02±0.64
Gyroscope	93.31±0.56	9.06±0.84
Acc & Gyro	99.20±0.55	9.23±0.74

From Table 5., the system with both accelerometer and gyroscope can provide more features of the activities, and therefore provide higher accuracy of recognition. From Table 6, it is evident that the system with a dual-sensor node's network can provide higher accuracy than a single node. There is no big difference in operation time since the time-consuming computations are distributed to the sensor nodes.

Table. 6. Accuracy and operation time of single-sensor node and dual-sensor nodes network.

Sensor nodes	Accuracy (%)	Operation Time (ms)
Single-node on wrist	98.18±0.59	9.54±1.35
Single-node on elbow	97.61±0.96	9.21±0.77
Dual-node on wrist and elbow	99.20±0.55	9.23±0.74

There are related studies of IMU-based HAR reported in the literature, such as CNN based method for daily activities including walking, upstairs, downstairs, sitting, standing, and lying with an accuracy of 93.77 % [12], least-square SVM for 10 daily activities and 11 sports activities with accuracies of 98.23 % and 99.55 % respectively [22], kernel extreme learning machine for 5 dynamic daily activities and 1 static activity with an accuracy of 98.69 % [23], and CNN for 18 kinds of sports activities with an accuracy of 96.2 % [12]. Although the results are obtained with different sensors devices, activities, and experimental settings, the accuracy of the methods presented in this investigation is competitive.

5. Conclusion

A miniaturized wearable HAR sensor node architecture integrating MEMS-IMU, MCU, and BLE for an unobtrusive wearable body area sensing network is proposed. To reduce the transmission time of raw sensor data and relieve the computational burden of the host machine, the computational tasks of pre-processing and feature extraction are distributed in the sensor nodes and the classification and application-specific tasks are allocated to the host machine. The CV-KNN and PSO-SVM classification algorithms are employed for decision-making. By mounting two sensor nodes on the wrist and elbow, the motions of virtual writing of numbers 0-9 with a hand in the air are chosen as the activity for experimental studies. The proposed hardware and algorithm system is tested in the experimental studies with 10 participants each repeating the 10 virtual writings 5 times. The results demonstrate that the proposed hardware/software co-design for integrated sensing and computing can successfully achieve the wearable HAR functions, and the PSO-SVM outperforms the peer algorithms in accuracy and operation time. The low-power wearable sensor network-based HAR system presented in this paper can find potential application in a smart home for intelligent home appliance control, in rehabilitation for patient health recovery evaluation, and in sports assistance for kinematic analysis of human body parts in sports.

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