

A Study of Wearable Accelerometers Layout for Human Activity Recognition

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ABSTRACT

For devices of human daily activity detection, accelerometer, can sense acceleration signals with different characteristics according to different parts of the human body. In this paper, we present a framework to investigate the impact of the number and placement of accelerometers on human daily activity recognition. 17 different parts of body are equipped with accelerometers, and examined. Multistage and multiswarm discrete particle swarm optimization (MSMS-DSPO) algorithm is developed to search the optimal sensor combinations on basis of number of sensor's demand. Additionally, user preferences of wearable sensor wearing is investigated and the motion recognition of involved place is analyzed as well. Thus, different sensor layouts for specific activity category recognition are provided, which is beneficial for user to arrange the devices on their body according to number requirement, activity type, preference or physical condition in an activity recognition application.

Author Keywords

Human motion recognition; Particle swarm optimization
Sensor layout; Wearable accelerometer

CCS Concepts

•**Human-centered computing** → **Ubiquitous and mobile computing**; *Ubiquitous and mobile computing design and evaluation methods*; Ambient intelligence;

INTRODUCTION

As rapid development of non-visual based motion recognition system, wearable sensors are normally adopted to gather the motion information from the object. The sensors are equipped on the obvious body parts for detecting the significant human physiological or physical data. Due to the convenience of the device, wearable equipment for human related motion or gesture recognition has assisted human effectively at indoors and outdoors scenarios [5], [4]. For human activity monitoring,

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the acceleration signal is capable of reflecting the information regarding the activity of daily living (ADL) being conducted, and accelerometer is generally adopted as the sensing device to acquire the information of vast majority of human motion.

As a practical application, the consideration of applied object conditions and preferences for sensor wearing is necessary. For example, in rehabilitation case, the applied objects' bodies differ in degrees of injury received and thus more options for sensor placement is necessary for those. Investigation of the number of wearable sensors used and positions on the human body is of importance for user to balance their own preferences and actual situations of recognition accuracy. Furthermore, a favorable sensor position can help reduce the requirement of system algorithm as well and contributes to accuracy improvement.

RELATED WORK

Different parts of the human body contain various acceleration information and thus generating various recognition effect. Many researchers have studied the influence of placements of sensors on recognition result. Atallah et al. [1] introduced the optimal sensor placement with regard to specific activities through k-Nearest Neighbor (KNN) classifier. The work examined 14 kinds of human ADLs, 6 body placements as well as different vital features for a classifier. Whereas only the impact of single accelerometer is examined in related experiment and the choices for more sensors are not provided in their work. Gjoreski et al. [3] investigated the recognition of 8 activities with 1 to 3 sensors used and 2 types of equipment (accelerometer and accelerometer/gyroscope combination) are involved in their work. Cleland et al. [2] utilized support vector machine (SVM) to establish the activity recognition system, and evaluated the best sensor combinations of 6 different human positions. Result revealed that basically 2-sensor combination would satisfy the precision requirements in most cases. Even though the related works had studied the number of sensors for activity detection, there has been little comparison of different placement and relatively less examined position of human body.

SYSTEM DESIGN

Experiment configuration

In the experiment, there are 17 different positions on the human body for corresponding accelerometer placed. The inertial device XSens MVN is adopted as the accelerometer. As

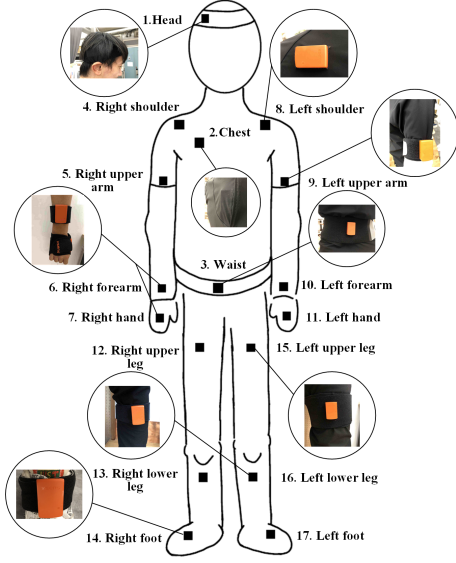


Figure 1. Position process for not repeating (3-sensor as an instance)

shown in Figure 1, sensor placements include the head, chest, left shoulder, right shoulder, waist, left upper arm, left forearm, right upper arm, right forearm, left hand, right hand, left upper leg, left lower leg, left foot, right upper leg, right lower leg and right foot. 10 subjects are involved in corresponding experiments to execute 10 different kinds of daily activities. Conducted ADL can be divided into 3 types, i.e. the static activity (standing and lying), dynamic activity (walking, running, going upstairs and going downstairs.) and transitional activity (sitting-to-standing, standing-to-sitting, squatting-to-standing and standing-to-squatting.). Both static and dynamic activities are performed by subjects for duration of 90 seconds at a time and transitional activities in set of 15 repetitions. Relevant motions are recorded by XSens system for annotation.

Related data processing

To recognize the activities that people are conducting, one of the effective approaches, machine learning has attracted much attention due to its intelligence. According to the work of Rosati et al. [6], 4 different classifiers (SVM, KNN, Decision tree and Feedforward neural network) were evaluated and the SVM can present the best recognition accuracy among them. Consequently, SVM is selected as the classifier in our system to recognize the human ADL.

Sampled acceleration signal is firstly segmented by sliding window method. The window length in our work is set to be 4s with an overlap of 2s for ensuring the continuity of motion. Features selected are from 3 axes of each sensor and include the mean value, variance, standard variance, 75th percentile, inter-percentile, mean and median value of power spectrum and Shannon entropy.

OPTIMAL SENSOR LAYOUT EVALUATION

Although 17 different positions on human body are involved to place the wearable sensors, considering the practical application, it is more valuable to investigate the corresponding sensors on body with the number of 4 or fewer. Thus, the multiswarm and multistage discrete particle swarm optimization (MSMS-DPSO) algorithm based on swarm intelligent searching method is developed in this paper. MSMS-DPSO is designed according to the thought of particle swarm optimization (PSO), which imitates the behavior of birds foraging. Relevant equations are shown in formula (1), (2) and (3).

$$v_{n+1}^i = w \cdot v_n^i + c_1 r_1 (P_{best}^i - x_n^i) + c_2 r_2 (G_{best}^i - x_n^i) \quad (1)$$

$$x_{n+1}^i = x_n^i + v_{n+1}^i \quad (2)$$

$$x_{n+1}^i = \begin{cases} \lfloor x_{n+1}^i \rfloor & \text{if } x_{n+1}^i - \lfloor x_{n+1}^i \rfloor < 0.5 \\ \lceil x_{n+1}^i \rceil & \text{if } x_{n+1}^i - \lfloor x_{n+1}^i \rfloor > 0.5 \end{cases} \quad (3)$$

Where x is the position of each particle. i and n represent the dimension that the particle in and discrete time, respectively. Besides, each particle has its own velocity, which is expressed by v . Equation (1) is the velocity updating equation, consists of three parts, namely, itself part, ‘individual’ part and ‘social’ part. During the iteration period, particle is judged via the fitness value of goal function. Position x is updated by equation (2). P_{best} is the best fitness value from history of a particle. Similarly, G_{best} represents the best value among the history of all particles. In order to introduce the characteristic of randomness, r_1 and r_2 are random operators and produced randomly between (0,1). c_1 and c_2 , as the operators of ‘individual’ and ‘social’ part.

Thus, the principle of PSO can be concluded that during the iteration the velocity and position of particle are constantly updated through both the characteristics of randomness and convergence considering. Following the updating process, the particles are likely to converge to the best solution which has optimal fitness value. In our case, fitness function is the relationship between the sensor location and the recognition accuracy of human activity. Optimal solution indicates the sensor placement that the system can obtain the maximum accuracy. Because the sensor location numbers (as indicated in Figure 1) are in discrete space, the PSO is able to be discretization so that equation (3) is introduced to allow the calculated position to round to integer number.

To apply the algorithm, the position of each particle is defined as the sensor location number and dimension is the requirement of used sensor amount. Designed MSMS-DPSO implement the optimization within two periods: intragroup optimization and whole swarm optimization. For first optimization period, different swarms carry out PSO optimization in their own swarm. The global and local best position are both defined within their own group and different swarm’s best position does not affect each other. The fitness value is calculated once any of dimension’s position of a particle has been changed. After the first stage, the participated particles in second stage are the global best particle from each swarm. In this period, calculation of fitness value is completed when a particle’s position in different dimensions have all been updated.

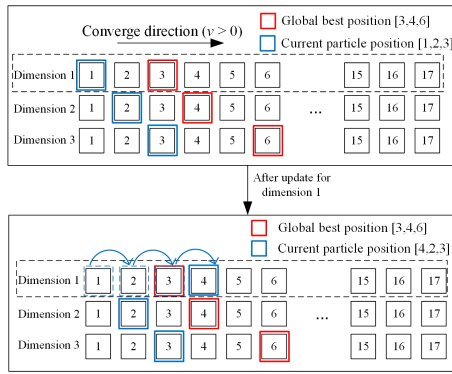


Figure 2. Position process for not repeating (3-sensor as an instance)

Sensor number	Optimal position	Accuracy
1	Right shoulder	88.614%
	Waist	87.733%
	Left shoulder	87.686%
2	Waist+Chest	93.555%
	Waist+Head	92.683%
	Right shoulder+Waist	92.659%
3	Waist+Chest+Right upper arm	94.572%
	Waist+Chest+Head	94.544%
	Waist+Chest+Left shoulder	94.298%
4	Waist+Chest+Head+Right upper arm	95.126%
	Waist+Chest+Head+Left upper arm	94.828%
	Waist+Chest+Right upper arm+Left upper arm	94.714%

Table 1. Acceptable optimal sensor combinations for 1 to 4 sensors

It is noticeable that during the updating period, the avoidance for non-repetition of each particle is necessary. The particle's positions in all dimensions should be different. Hence, we defined the process according to the convergence velocity of each dimension, to realize non-repetition of dimension. Figure 2. presents the relevant repetition avoiding process; in which velocity is positive as an instance.

At the beginning, the algorithm initializes 9 particles and 3 as a swarm. It indicates that a total of 27 particles will be involved in first intragroup optimization and 9 particles in second optimization period. The first-dimension position is specified as $2P-1$ ($P=1,2,\dots,9$) and remaining positions are randomly produced and do not repeat with first dimension's position. Two border particles ($[1,2,3,\dots,N]$, $[17,16,15,\dots,17-N+1]$, N is dimension) are defined as well.

For evaluation, at the first, the single sensor is utilized in turn to obtain the highest average classification result as the best position for single sensor via 10-fold cross validation. And subsequently adopting the MSMS-DPSO algorithm to seek other optimal sensor combinations. The convergence condition for intragroup optimization stage is set as reaching the maximum iteration times: $N+1$. In second period, when all the particles' positions converge into the same best position the algorithm stops operating. To avoid the randomness of cross validation, the algorithm is required to performing 3 times to calculate the average value as the result. Top three combinations ranked are summarized in Table 1.

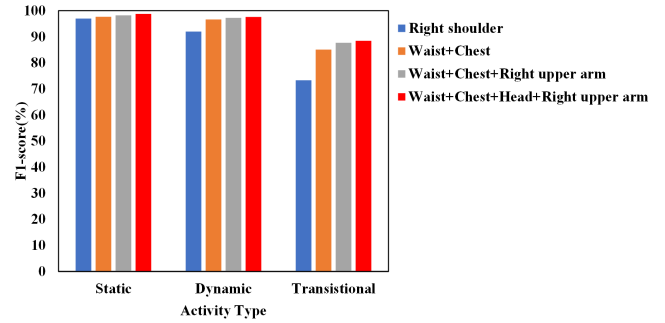


Figure 3. F1-score of optimal two-, three- and four-sensor combination related to three types of activity

RESULT DISCUSSION

Optimal sensor layout and related recognition performance

With MSMS-DPSO algorithm applied, the optimal sensor combinations with different used number among 17 different human parts is able to be figured out. Figure 3. gives the F1-score of optimal 1, 2, 3 and 4 sensors' combinations for recognizing three types of ADL.

From the figure, with more sensors used the performance of recognizing transitional activity is improved significantly. Related F1-score of one sensor used for classifying, from 73.31% increases to 88.49% with 4 sensors used. The increase of sensor number also leads to classify the dynamic activity more effectively, i.e. from 92.04% (1-sensor) to 97.65% (4-sensor). However, for static type, the accuracy improvement is not such obvious. Only up to 2% increase is caused with sensor number raising. But one sensor with optimal position (right shoulder) has enabled the system to achieve the accuracy of 96.98%.

In Table1, it is worth noticing that the sensor placement on upper body is likely to allow the system to obtain an acceptable result. We found that signals from lower body normally have less ability to identify the activity of going up or downstairs, as well as transitional activity. Normally 2 sensors are enough for system to classify the ADL in most cases, which is consistent with the work of [2]. Whereas, if a better result is required especially for recognition of transitional activities, increasing the number of sensors can be a favorable solution.

User preferences for position of wearable sensors

Figure 4. and Figure 5. show the result of investigation of the user preferences of accessories wearing on body. 100 people (50 female and 50 male) are involved in online questionnaire and objects' age are between 20 to 60.

Figure 4. shows that almost half (53%) of people would like to wear the relevant device on their wrist. In addition, 14% of people are willing to attach the device on the head or ear and 11% would like the accept electronic sensors in the form of glasses or attached to glasses. Nevertheless, for belt, shoes, shoulder and chest can not attract much attention from users.

