# Wearable Accelerometer Optimal Positions for Human Motion Recognition

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***Abstract*— An intelligent human activity recognition system is influenced to some extent by sensor placement. In this paper, the number, and placement positions, of wearable accelerometers have been investigated to determine their influence on a human activity recognition system. Given 17 possible human sensor placements, we developed a multi-stage and multi-swarm discrete particle swarm optimization algorithm to explore the optimal sensor combination for various required sensor amounts. Relevant experimentation involved 10 different human daily activities, achieving an average prediction accuracy for a 4-sensor optimal combination of 95.12% via support vector machine classifier. The number and corresponding placement of sensors required for activity recognition have also been provided in this paper.**

**Keywords— amount and position, motion recognition, particle swarm optimization, wearable accelerometer**

## I. Introduction

Since human acceleration has been determined to provide information on the vast majority of human daily living activity (ADL), researchers have applied relevant systems to facilitate people's lives [1]. Obvious characteristics of different activities can be reflected through different parts of the body, causing differing information depending on sensor placement. Moreover, a favorable sensor position can reduce system algorithm requirements and contributing to performance improvement. The sensor placement must be considered as the chief step for both action recognition and the applied body situation. Therefore, a multistage and multi-swarm discrete particle swarm optimization (MSMS-DPSO) algorithm is proposed to investigate the optimal sensor combination among 17 sensors for varying sensor amount requirements.

## II. Experiment Design

### A. Experiment configuration

Acceleration data will be captured from inertial sensor (Xsens ltd., Netherlands) placed at 17 different locations. These locations are the head, chest, left and right shoulders, waist, left and right upper arms, left and right forearms, left and right hands, left and right upper and lower legs, and left and right feet. Fig. 1 shows the related body sensor layout. Ten subjects will be involved in the experiment. They will be asked to perform 10 different activities (i.e., standing, lying, walking, running, going upstairs, going downstairs, sit-to-stand, stand-to-sit, squat-to-stand and stand-to-squat). The last four actions will be performed 15 times and all remaining activities will be performed for 90s. The experimental motions will be recorded using an Xsens MVN system for annotation.

### B. Data Interpretation and classiffier selection

The sensed 3-axes acceleration signal will be processed with sliding window method. The window size is set to be 4 s and overlapping length is 2 s. The eight selected features are the mean value, variance, standard variance, 75th percentile, inter-percentile, mean and median values of the power spectrum, and the Shannon entropy value. Due to the superiority of the support vector machine as a classifier of human ADL recognition systems, the support vector machine will be adopted to classify different activities [2].

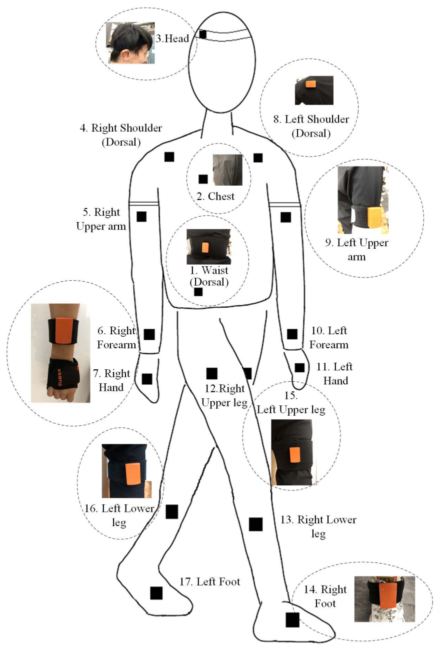


Fig. 1. Worn sensors on human body (with portion of practical sensors)

## III. Methodology

A heuristic algorithm is introduced to determine the optimal sensor combination among 17 different positions. Discrete particle swarm optimization (PSO), as a swarm intelligence algorithm, solves a series of discrete space optimization problems. For an *N*-dimension space, discrete PSO needs to generate a series of initial solutions before updating each particle's position via a novel velocity, as expressed in equations (1), (2), and (3). A detailed coefficient description was presented in [3].

$$v^i_{n+1} = w \cdot v^i_n + c_1 r_1 (P^i_{best} - x'^i_n) + c_2 r_2 (G^i_{best} - x'^i_n) \tag{1}$$

$$x^i_{n+1} = x'^i_n + v^i_{n+1} \tag{2}$$

$$x'^i_{n+1} = \begin{cases} [x^i_{n+1}] & if \ \ x^i_{n+1} - [x^i_{n+1}] < 0.5 \\ [x^i_{n+1}] + 1 & if \ \ x^i_{n+1} - [x^i_{n+1}] > 0.5 \end{cases} \tag{3}$$

As this research aims to determine the optimal sensor combinations among 17 sensors for different sensor amount

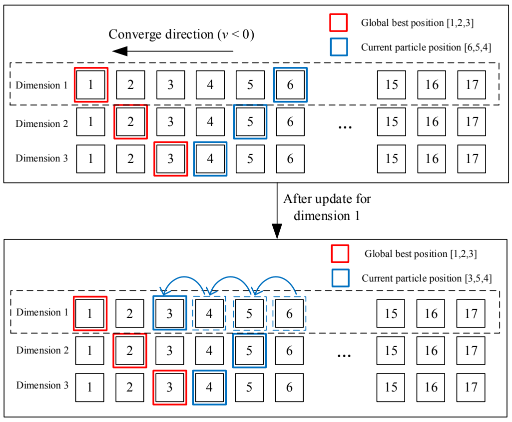


Fig. 2. Position process for not repeating, $v$<0 as an instance (3-sensor)

requirements, sensor positions are numbered from 1–17 (Fig. 1) and the dimensionality can be represented by the required amount of sensors.

The significance of discrete PSO avoids repeating particle positions in different dimensions while guaranteeing randomness and convergence. In this paper, the principle of non-repetition for each particle is designed according to each particle's velocity, as presented in Fig. 2. Positions are processed according to converging direction, i.e. the positive and negative velocity.

An MSMS-DPSO design can be divided into two periods: intragroup optimization and whole swarm optimization. To begin, the algorithm initializes nine particles and three of initial particles as a swarm. The first-dimension position is indicated as $2P$ - 1 ($P$ = 1, 2…9) and remaining positions are produced randomly without repeating the first dimension's position. Two border particles ([1, 2, 3…, $N$] and [17, 16, 15…, 17 - $N$ + 1], where $N$ is the dimension) are defined as well.

During the intragroup optimization period, different swarms carry out PSO optimization for their own swarm. The global and local best positions are defined within their own group, and each swarm's best position does not affect any other swarm. The average classification accuracy is calculated once the dimensional position of any particle changes. After intragroup optimization, the global best particle from each swarm participate in whole swarm optimization, illustrating the optimal position among all swarms' global best positions. In this period, fitness calculation is completed when all of a particle's dimensional positions have been updated.

## IV. Result

Considering the practical application, the investigated sensor combinations range from 1-sensor to 4-sensor. Single sensors were utilized first to obtain the highest average classification result (best position) for a single sensor via 10-fold cross validation. The subsequent adoption of the MSMS-DPSO algorithm determined the optimal combinations. The convergence condition for intragroup optimization was set as reaching the maximum iteration of $N$ + 1 times. During whole swarm optimization, once all the particles' positions converged into a matching best position, the algorithm stopped operating. The results are displayed in Table I. And the related F1-score results are given in Fig. 3.

TABLE I. Combination Result for Different Sensor Amount

| Sensor number | Position | Accuracy (%) |
|---|---|---|
| | Right shoulder | 88.83% |
| 1 | Waist | 87.73% |
| | Left Shoulder | 87.68% |
| | Waist +Chest | 93.55% |
| 2 | Waist+ Head | 92.68% |
| | Waist+ Right shoulder | 92.66% |
| | Waist + Chest +Right upper arm | 94.57% |
| 3 | Waist + Chest +Head | 94.54% |
| | Waist + Chest +Left shoulder | 94.29% |
| | Waist + Chest + Head +Right upper arm | 95.12% |
| 4 | Waist + Chest + Head +Left upper arm | 94.83% |
| | Waist + Chest+ Right upper arm +Left upper arm | 94.71% |

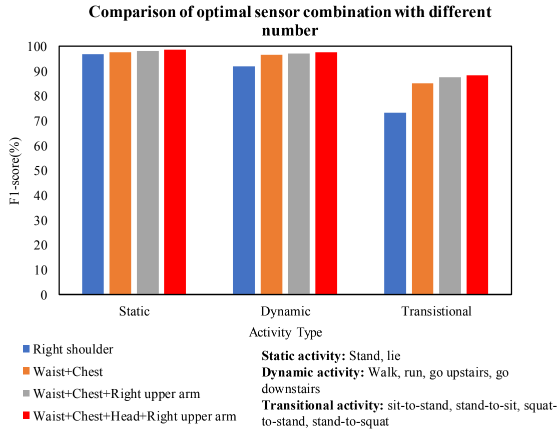


Fig. 3. Comparison of optimal sensor combinations with F1-score of optimal 1-, 2-, 3- and 4- sensor combinations.

## V. Conclusion

The results indicate the upper body sensor can generate a preferred result and normally two sensors can satisfy most recognition cases. When more sensors are used, an obvious improvement is brought to transitional activity recognition. While increasing the number of sensors does not lead to a significant recognition rate increase for static activity. To the best of our knowledge, this is the first time the impact of the number and position of sensors on human ADL performance recognition has been investigated. The MSMS-DPSO algorithm proposed in our work can find optimal combinations of varying sensor numbers, decreasing the operation time compared to testing all possible combinations.

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