Optimal Sensor Position: Exploring the Interface Between the User and Sensor in Activity Recognition System

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ABSTRACT

Human activity recognition systems combined with machine learning normally serve users based on the fixed sensor position. Uniform sensor position normally cannot satisfy the user's demand according to different conditions. In this paper, we recognized the sensor position as an interface between the user and sensor system. We designed the optimization scheme to generate the best sensor position for activity recognition system. The user can indicate his/her preferred or disliked position and sensor numbers and the proposed optimization evaluates which position or positions combination can generate best accuracy under user's preference. With the experiment, the proposed scheme can be employed to discover the optimal position to help the HAR system in a simple and customized way.

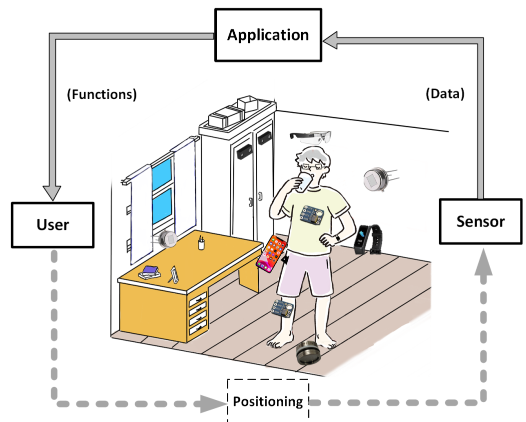

Figure 1: Concept between the user and sensor-based HAR system

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; *Ubiquitous and mobile computing systems and tools.*

KEYWORDS

Activity recognition, interface, optimization, sensor position

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1 INTRODUCTION

With enormous efforts on the human activity recognition (HAR) system, developed systems gradually shift to maintain the characteristics of high-performance, lightness, and universality. Infiltrating the people's daily lives, the HAR system presents the benefits among all aspects with ubiquitous sensing via the machine learning (ML) network. As a data-driven based technique, ML relies on the training data stream to show a satisfied accuracy of classification. Following the classical design pipeline of an HAR system, the designer or developer normally installed the sensor at the designated locations (the human body surface or ambient) to obtain the data. Therefore, the ML classifier is built based on such position specific dataset and the sensor positions are fixed in the post application.

From the HAR related HCI community, past researches concentrated on the application of recognition and exploring more possible input modalities. Both perspectives serve the user in a pervasive way. However, the interface between the user and sensor (i.e., the applied position of the sensor) may be rashly overlooked (as shown in Figure 1). Currently, at the device level, adopted sensors in HAR systems are gradually combined with the ubiquitous equipment to provide convenience, such as smartphone and watch. However, fixed positions of employed sensors are not always working for all users. For wearable types, the subject may present different body conditions and different preferences for sensor wearing. For example, during rehabilitation with an activity record of elderly and patients, for those with upper limbs injuries (like left limb) who must choose to wear the sensor on lower limbs. Other locations combined with accessories like hair bands, the ears, elbows, belts, chest pockets, necklaces, knee supporters, or shoes also can be effective for sensor [3]. Additionally, for non-wearable types, the effective detection area is fixed by the installation of sensors. However, indoor design of HAR systems generally takes along with plenty of potential locations to place the sensors. The selection of sensor position is supposed to balance the design convenience and system performance.

The investigation most close to the position related issue is the development of position-aware classifiers for HAR systems [9, 11]. The pre-trained different position based classifier would conduct

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the targeted recognition according to the sensor's wearing position. However, these pipelines are at application level, and are difficult to follow the user's preference and utilized during the design period. And when the potential positions increased it is hard to pre-train all the position-based classifiers. Oriented to different people, the requirements related to the sensor positions may also be different. The developer aims to explore a location that the most significant signal variation caused by human activity exists. For usage, the user is preferred to have a more flexible position interface, which means that more options can be generated to satisfy the different individual's preference or body condition. Thus, two basic questions are proposed based on the sensor positions in HAR systems:

(1) *Can I have more options for sensor placing to follow my preference*?
(2) *Where is the most significant position to present the highest accuracy in a given ML network*?

Hence, we may envision that, to explore the sensor's position can be a novel interface between the user and HAR system and improve the adaptability of application. This study is going to discuss the sensor position in HAR system development, and aims to improve the interaction from the HCI aspect.

2 CLARITY AND RELATED WORK

Actually, either to obtain more choices reflecting the user's preference or to find a significant position generating highest accuracy, the core can be summarized as an optimal problem. The goal function is a relation between the selection position and ultimate recognition accuracy. And the user's preference is indicated as the constraint conditions. To answer the question, is a way to seek a solution that can enable the goal function to maintain the maximum value as well as satisfy the constraint conditions.

To explore the position with highest accuracy produced, effective areas and potential positions can be optimized to find the best location. In the HCI community, Kim et al. [5] has announced they conducted the first systematic examination regarding sensor placement for a computer mouse. For other fields, many researchers have studied the influence of sensor positioning from the aspect of the human body [6] and structure monitoring [8]. For widely used wearable accelerometers, Kunze et al. [7] compared positions of accelerometers placed on the body and proposed the method to eliminate the influence caused by various locations. Cleland [1], Olgun [10] and Gjoreski [4] all tested sensors worn on the body with different positions and numbers. However, their work only offered the trend of accuracy respecting disparate positions and numbers, instead of answering where the best positions were for activity recognition. To optimize the sensor's location for detection, it is more widely used in building/structure health monitoring. The sensor can be placed in an extensive space inside a building, like our living room. Using an optimization algorithm, such as a Bayesian network [2] and heuristic algorithms [12, 14], has been identified as effective tools for solving such problems.

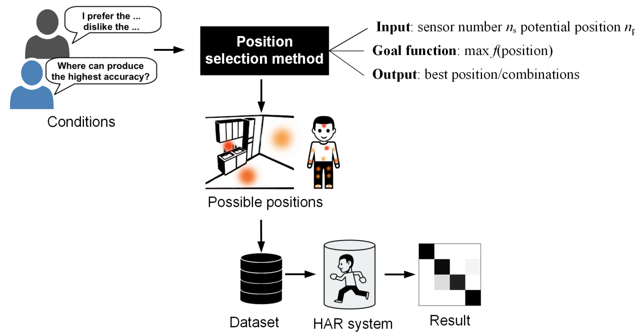

Figure 2: Description of sensor-position based HAR design

3 METHODOLOGY

3.1 Problem description

Proposed questions has been transferred into an optimization problem to derive the optimal solution which is able to generate and train a classifier with best performance. To discuss the effect of sensor position on HAR performance, one key premise needs to be clarified is that optimal sensor position depends on each specific HAR system. We describe the problem in Figure 2. The sensor position selection is conducted during the design process that is before the training. Thus, with different design minds the characteristics of collected dataset are different.

3.2 Classical design-orientation

For common HAR system design, the developer normally followed the experience or trial-and-error approach to generate the dataset. For example, to develop an inertial device based HAR system, the usually considered position emerges with the wrist and thigh. This is inspired by the employed electronics. When adopting the ambient sensors, such as infrared pyroelectric sensor and distance sensor, such sensors normally are attached to the surface of ceiling, wall or daily items. And generally the sensors are densely placed to increase the robustness of the developed system.

We can recognize this method as a type of 'random selection'. The developer does not need to spend a lot of time on sensor position selection, merely adhere to the previous work or experience. Although the selected positions are probably not the optimal, the simple process enables such methods to be more common in related communities.

3.3 Firefly searching to generate the optimal sensor positions with user conditions

Besides the popular positions, users normally have different preferences about the sensor position. We take the wearable accelerometer-based system as an instance. In addition to the popular position, like wrist or thigh on the body, some other positions may not be suitable for sensor placing because the performance based on such positions is poor even though such positions cater to the preferences of users. To tackle this problem, adding additional sensors on other acceptable positions is capable of making an improvement. Therefore, an optimization problem that finds the best position combination under the user conditions therefore emerges. The problem is identified as an NP-hard combination problem. The baseline method is testing all the possible combinations of positions and output the best position with maximum accuracy produced. Nevertheless, when the potential position and required sensors number amount is large, the baseline method is going to cause the curse of computational cost.

Heuristic searching method is a solution to produce the global optimal result with a reasonable time cost. One of the heuristic searching methods is the swarm intelligence approach which imitates the natural behavior from the biological population in nature [13]. In this work, we designed an optimization scheme based on firefly algorithm in discrete domain (DFA) to find the optimal solution under the user conditions. The firefly algorithm imitates the motion of the firefly population, i.e., fireflies have the behavior of flying towards the light source. A firefly will be attracted to each other regardless of the sex. And the attractiveness is proportional to their brightness whereas the less bright firefly will be attracted to the brighter firefly. While the brightness of two fireflies are the same, the firefly will move randomly. Some definitions of function and variables are given as below.

(1) Dimension D: applied sensor numbers;
(2) Swarm position x: the sensor position coding; from 1 to n. n indicates the total position amount;
(3) Population N: participants fireflies number;
(4) Fitness function f: the relationship between the specific position-based dataset and recognition accuracy by cross-validation;
(5) Brightness: accuracy;
(6) End condition: when the iteration times reaches the maximum times;

At the beginning, the algorithm distributes the initial fireflies evenly, and then generates fitness values of each firefly, the initial best position. During the iteration, each firefly's brightness is calculated at the first. According to the brightness value, the distance d is obtained through equation (1).

$$d = \sqrt{x_i^k - x_j^k} \tag{1}$$

Where x_i and x_j indicate different two fireflies. k represents the current dimension, $k\in$ [1,2..D] To ensure that the adjustment of firefly's position is not large, we define the mapping factor by equation (2).

$$m = \frac{\varepsilon\left(d - x_{upper}\right)}{x_{upper} - x_{\text{lower}}} \tag{2}$$

$$d^* = m \cdot d \tag{3}$$

Where ε is the controlling factor to adjust the step for each movement. In this instance, we took it as 2. $x_{upper} = n$ and x_{lower} =1 are the boundary of each firefly. The position updating function is given in equation (4) which indicates that the firefly x_i is moving the brighter one x_j.

$$x_i^k(t+1) = x_i^k(t)\left(1 - \beta\left(d^*\right)\right) + x_j^k \cdot \beta\left(d^*\right) + \alpha(\text{ rand } - 0.5) \tag{4}$$

$$\beta = \beta_0 e^{-\gamma d^{*2}} \tag{5}$$

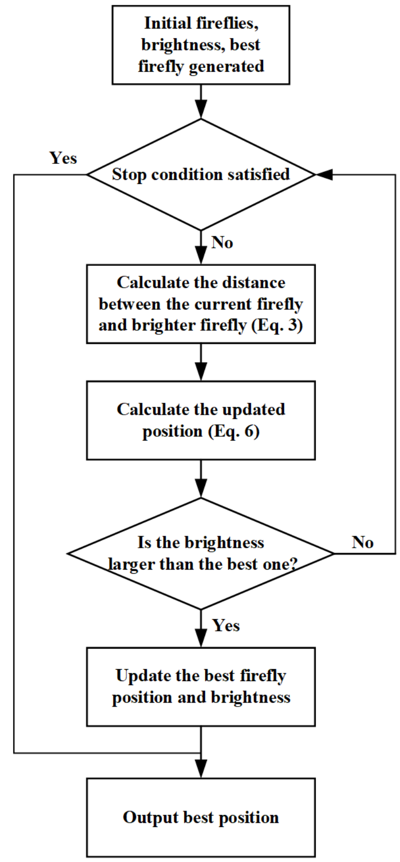

Figure 3: Designed DFA algorithm working flow

Where the β is a function of distance d^* and calculated by equation (4). The γ is called absorption coefficient and is taken by 1. β_0 is the initial firefly attractiveness value. α controls the degree of random walk. After calculation, we need to take the integer value of the obtained result as the updated firefly position by equation (5).

$$x_k'^i = \begin{cases} \left[x_k^i\right] & if\ x_k^i - \left[x_k^i\right] < 0.5 \\ \left[x_k^i\right] + 1 & if\ x_k^i - \left[x_k^i\right] > 0.5 \end{cases} \tag{6}$$

As a new firefly position is generated, the brightness is supposed to be calculated to update the global best one.

The entire process is shown in Figure 3. It is noticeable that due to the discrete characteristic of each position number, it is significant to avoid the position repetition among different dimensions (the same position can not be placed in more than one sensor). We referred to the method of [12] to skip the repeated position.

With proposed DFA based optimization when the required sensor number is higher, the computational cost will obviously decrease. The user could indicate the preferred or disliked positions as input conditions, and the optimizer conducts the optimization with restrictions considered. As stated before, the optimization process is based on the position's encoding. Thus, we also could realize mapping the user conditions into optimization via the encoded

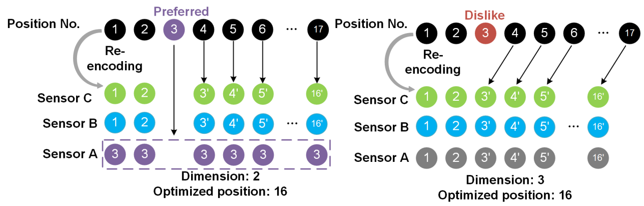

Figure 4: The position encoding process regarding how to map the user's preferred and disliked position

position. Figure 4 presents the position number regarding mapping the user conditions during optimization.

4 EXPERIMENT AND APPLICATION

In the experiment part, we examined the methods for obtaining the sensor position to develop a HAR system. The presented accuracy and computation cost during position selection have been compared between different approaches.

4.1 Testing: explore the most suitable positions

We took a case as an instance of using the wearable accelerometer to recognize the human daily activity. Basically, we considered all the possible positions for sensor placing based on the body segments. The Support Vector Machine (SVM) classifier (RBF kernel with C = 1000) is employed. 10 people (5 male and 5 female) were recruited to perform the predefined ADLs and recorded. We used the Xsens sensor and via the MVN system to perform the annotation. Detailed feature selection and data segmentation method referenced the work of [12]. Other statements are shown as follows.

- Potential positions: 17 parts on the human body: *Head, chest, waist, right shoulder, right upper arm, right forearm, right hand, left upper arm, left shoulder, left forearm, left hand, right upper leg, right lower leg, right foot, left upper leg, left lower leg, left foot*;
- Recognized activity: *standing/walking/running/sit-to-stand/stand-to-sit/squat-to-stand/stand-to-squat/upstairs/downstairs/lying*;
- User conditions: preferred to the *waist* disliked the *Head*; Required sensor numbers less than 3;

We subsequently executed different methods in terms of selecting the sensor position to build the corresponding HAR system. The result is presented in Table 1, and the cost indicates the computation times to obtain the selected position(s).

Through the experiment, the DFA is capable of discovering the optimal sensor positions under the user conditions compared with the classical design pipeline following the popular positions on the body. And also the DFA is demonstrated to get the global solution with less computational cost compared with baseline method.

4.2 Application: combined with simulation dataset to improve design process

As the case presented above gives a scene to evaluate the most suitable position of wearable sensors among the whole body parts. One of the big premises is to collect the samples from all body segments in the real-world. In this part, based on the virtual environment, we can simulate the daily scenario and items virtually. With motion capture data input, the human model is able to be virtually presented as well. Based on this idea, we utilized the Unity3D as a basic platform and the DFA optimization scheme to conduct a design process for a distance sensor-based HAR system, showing the effectiveness of the proposed DFA searching method. Descriptions are given as follows.

- Applied scene: bathroom
- Applied sensor type: distance sensor
- Recognized activity: *washing hands*, *washing face*, *brushing teeth*
- Recognition process: segment the data – transfer into grayscale figure – extract the texture feature – training the SVM classifier
- Working flow: virtual environment data collection – sensor position optimization – training the classifier – mapping into real world to recognize the activity
- User conditions: use less than 20 sensors

Related process is shown in Figure 5. As an illustration, we did not realise more details about utilizing the virtual dataset to train the classifier. Only the optimized result is presented to validate the utilization of proposed DFA algorithm. For this type of application, the optimized object will find the installing positions of sensors under the preferred sensor number. We assumed a 7*10-sensor mounted on the wall above the washbasin (as shown in Figure 5(a) and (b) as the original area. A total of 70 sensors are used, and the interval between each sensor is 5 cm. We arrange the 70 sensors into 24 sub-boards. The first type contains five sensors, and the second has seven (cf. blue and red blocks in Figure 5(c)). According to the processing, the optimal placement of relevant sensors is given under the specific number of sub-sensor boards.

If only one sub-sensor board is used, the best one is: [0, 1, 2, 3, 4]. The simulation accuracy is 90.86%; if two sub-sensor boards are used, the best are [0, 1, 2, 3, 4] and [5, 6, 7, 8, 9]. The simulation accuracy is 92.06%; if three sub-sensor boards are used, the best are [0, 1, 2, 3, 4], [5, 6, 7, 8, 9] and [3, 13, 23, 33, 43, 53, 63]. The simulation accuracy is 95.23%.

The computational cost for each set via DFA is 24, 120 and 400 respectively. And the baseline method costs the computational times by 24, 275 (C_{24}^{2}) and 2024 (C_{24}^{3}). Thus, as required sensor numbers increased computational cost will be reduced obviously. With the optimal accuracy generated from DFA based on simulation data, the user therefore can selected the required sensors layout and accuracy indication according to demand. For example, the sensor [0, 1, 2, 3, 4] and [5, 6, 7, 8, 9] are selected and mapped into actual world to be installed (as shown in Figure 5(e)). And the real activity can be classified. In this case, in order to design an user-oriented HAR system, the DFA is employed to optimize the sensor number to save the space and ensure the accuracy to directly give the guidance of sensor positions. Combined with simulation/virtualization technique, the sensor position optimization is able to be an efficient way to reflect the user's condition into a customized HAR system.

Table 1: Test result from three methods

Method	Required number					
	1		2		3	
	Position/ Accuracy	Cost	Position/ Accuracy	Cost	Position/ Accuracy	Cost
Classical design	Waist/ 88.01%	1	Wrist (left) + Waist/ 88.95%	1	Wrist (left) + Left upper leg + Waist/ 87.56%	1
DFA	Waist / 88.01%	1	Waist + Chest/ 93.56%	16	Waist + Chest + Right upper arm/ 94.76%	60
Test all combinations	Waist / 88.01%	1	Waist + Chest/ 93.56%	16	Waist + Chest + Right upper arm/ 94.76%	C_{15}^{2}= 105

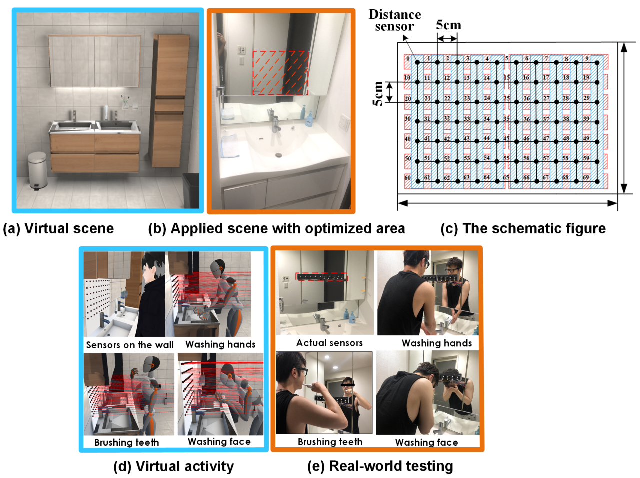

Figure 5: Description of designing a specific HAR system with position interface and simulation technique. (a) Virtual scene, the bathroom. (b) Actual applied scene with red area of potential sensor position. (c) Schematic figure of the sensing area with 70 sensors. (d) Virtual activity to generate simulation dataset. (e) Real-world sensor placing and testing

5 DISCUSSION AND FUTURE WORK

In this work, we explored the sensor's position as an interface between the user and HAR system. Conventionally HAR system serves user with fixed position which is determined by experience. We therefore proposed the firefly algorithm based optimization scheme to figure out the best positions combination under the user's preference. The effectiveness of proposed optimization approach can be demonstrated by exploring the optimal positions in wearable accelerometer case. Combined with virtual simulation, the proposed scheme can also be used to improve the process of HAR system and balance the space design and user conditions. When the employed sensor's numbers increased, the effect for saving computational source will be more obvious.

However, the optimization still depends on the training dataset pretty much. To find the effect of different sensor positions on the HAR performance, the sensor data from each position is necessarily collected. Thus, the next step is supposed to combine the optimization with simulation technique to decrease the matters of gathering sensor dataset from the real world. We may envision that with the further development of virtual simulation of sensor data, more customized HAR system of the individual will be emerged through the interface of optimal sensor position.

6 ACKNOWLEDGEMENT

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