Evaluation Function of Sensor Position for Activity Recognition considering Wearability

Kazuya Murao
Kobe University
1-1 Rokkodaicho, Nada, Kobe,
Hyogo 657-8501, Japan
murao@eedept.kobe-u.ac.jp

Haruka Mogari
Kobe University
1-1 Rokkodaicho, Nada, Kobe,
Hyogo 657-8501, Japan
mogari3@stu.kobe-u.ac.jp

Tsutomu Terada
Kobe University/Japan Science and Technology Agency
1-1 Rokkodaicho, Nada, Kobe,
Hyogo 657-8501, Japan
tsutomu@eedept.kobe-u.ac.jp

Masahiko Tsukamoto
Kobe University
1-1 Rokkodaicho, Nada, Kobe,
Hyogo 657-8501, Japan
tuka@kobe-u.ac.jp

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Abstract
In the wearable computing environment, a computer provides many kinds of services by using the values from wearable sensors to recognize the user's movements or situations. In the research on activity recognition, accelerometers are attached on the user's body such as wrists, waist and, feet. Though researches on best sensor placement for context aware systems has been released thus far, they do not use enough number of sensors to really decide the best sensor placement. When using these context aware systems in our daily life, we also need to consider the discomfort that the user gets from attaching the sensors. The sensor might get in the user's way or feel uncomfortable for the user, however, as far as we know, the sensor's wearability is not taken into consideration in these researches. This paper proposes an evaluation function that scores sensor placement considering both recognition accuracy and sensor wearability, with twenty sensors on the user's body and thirty kinds of exercises including aerobic exercise, weight training, and yoga. Then we experimentally evaluated sensor placement, resulted in high degree of accuracy achieved without feeling stressful.

Author Keywords
Activity recognition, Accelerometer, Wearability

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
The downsizing of computers has led to wearable computing that has attracted a great deal of attention. Along with the progress in wearable computing, many contextaware systems with various kinds of sensors have recently been introduced, such as systems with accelerometers, gyroscopes, electromyographs[9], electrocardiograms[7], GSR (Galvanic Skin Reflexes)[6], and manually configured devices[3]. Contextaware systems are applied to many services i.e., health care[6]. recognition of workers' routine activities[5], and support during assembly and maintenance tasks[8]. Camera, GPS, gyroscope, and geomagnetic sensor are also known as devices that obtain location and motions, however these sensors have low wearability and accuracy, and cannot obtain both motion and static direction simultaneously. An accelerometer can obtain motion and static direction by sensing earth's gravity, and has high accuracy and high resolution, and is enough small to be attached on the body. For this reason, an accelerometer is the best device for activity recognition.

Multiple sensors are generally attached to the body to recognize many kinds of activities with high degree of accuracy. For example, distinguishes "standing" and "sitting" activities, values obtained from sensors on the hands or ankles are not discriminative, therefore sensors should be placed on the hip or thigh. On the other hand, a sensor on the wrist is needes for recognizing activity of uplifting objects. However, the users may get discomfort from attaching multiple sensors in their daily life. The important factors affecting user's discomfort including the following points.

- Low wearability
  - Sensors get in the user's way of activity.
  - Users feel a pain by scraping sensors with floor and wall.
  - Mounting of the sensors is annoying.
- Strange appearance
  - Sensors are attached to the body with a band, tape, cap, or wig, appearance of which may be strange.

The sensor's wearability has not been taken into consideration in the conventional studies. This paper focuses on the wearability, and propsoes a function that evaluates sensor placements considering both recognition accuracy and sensor wearability. With the evaluation function, users can find the best sensor placements meeting the required accuracy.

Related work
Conventional activity recognition systems use multiple sensors at fixed positions and appropriate sensor position is not discussed, while [4] measured the recognition accuracies of nine daily movements for all sensor combinations of five 3-axis accelerometers attached to a subject's wrists, ankles, and hip. The results show that recognition accuracies depends on the number of sensors and their combination. However, the number of sensor is small and the sensor positions does not includes the head, chest, and back. Moreover, most of the activities to be recognized use whole body, and activities that use specific

parts of body, such as gesturing, on which sensors affect the recognition accuracy are not included. [1] proposes a method to suppress deterioration of accuracy due to sensor displacement. This study reported that accuracy does not deteriorate by using the method even when sensors are attached to different position of the hand and leg, unless the difference is large. Though studies on sensor position have been carried out, all of them focus on recognition accuracy only, and, as far as we know, no study has investigated sensor wearability.

A design guideline for devices in wearable computing environment has been discussed in [2]. For the guideline, wearable devices should be designed considering the following points:

1. Placement
   Design for dynamic wearability requires unobtrusive placement.
2. Form language
   Design for the human body requires a humanistic form language.
3. Human movement
   Human movement provides both a constraint and a resource in the design of dynamic wearable forms.
4. Proxemics
   Design for human perception of size.
5. Sizing
   Size variation provides an interesting challenge when designing wearable forms.
6. Attachment
   Comfortable attachment of forms can be created by wrapping the form around the body, rather than using single point fastening systems such as clips or shoulder straps.
7. Containment
   Designing wearable objects generally requires the object to contain materials such as digital technology, water, food, etc.
8. Weight
   The weight of a wearable should not hinder the body's movement or balance.
9. Accessibility
   For any wearable it is important to consider the sort of accessibility necessary to render the product most usable.
10. Sensory interaction
    Sensory interaction, both passive and active, is a valuable aspect of any product.
11. Thermal
    There are three thermal aspects of designing objects for the body - functional, biological, and perceptual.
12. Aesthetics
    An important aspect of the form and function of any wearable object is aesthetics.
13. Long-term use
    The long term use of wearable computers has an unknown physiological effect on the human body.

In this paper, we focus on "3. Human movement" as a wearability for activity recognition and investigate the discomfort according to the movement with wearing sensors. "1. Placement" states that device area should have low movement/flexibility even when the body is in motion, which is applicable to all wearable objects but is not appropriate for wearable sensors capturing motions. Though "6. Attachment" is an important factor for wearable sensors, sensors are attached to the body by means as easy as possible. The other factors are not directory related to the sensor placement and are hardly considered for commercially available sensors. "12. Aesthetics" and "13. Long-term use" are also important factors, therefore we plan to investigate them as a future work.

Design of Evaluation function

Survey for wearability

One of the authors who attached twenty 3-axis wireless accelerometers (Wireless Technologies, Inc., WAA-006[1]) on her body, as shown in Figure 1, assessed the wearability of placement for thirty kinds of activities with three degrees: A, B, and C. Criteria of wearability is as follows: A is "unobstructed", B is "discomfort", and C is "obstructed". Name of the placement is listed in Table 1. The sensor was W39×H44×D12 [mm] and weighed 20 [g].

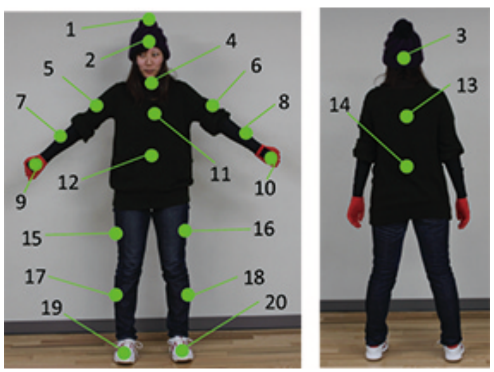


Figure 1: Sensor placement.

[1]Wireless Technologies, Inc., http://www.wireless-t.jp/.

Number	Placement	Number	Placement
1	Top of the head	11	Chest
2	Front of the head	12	Abdomen
3	Back of the head	13	Upper back
4	Neck	14	Lower back
5	Right upper arm	15	Right thigh
6	Left upper arm	16	Left thigh
7	Right lower arm	17	Right shin
8	Left lower arm	18	Left shin
9	Back of the right hand	19	Right instep
10	Back of the left hand	20	Left instep

Table 1: Sensor placement and index number.

She acted seven aerobic training (walking, jogging, bicycling, sit-up, back-extension, squat, and jump), eleven weight training using dumbbell[2] shown in Table 2, and twelve yoga poses[3] shown in Table 3.

The sensors on the head (1 to 3) are fixed with swim cap, the sensor on the neck (4) is fixed with rubber band, the sensors on both wrists (9, 10) are fixed with grove, the sensors on the feet (19, 20) are fixed with shoes. The sensors on the arm (5 to 8) and torso (11 to 14) are fixed with heat gear long sleeve T-shirt WCM3081 made by Under Armour[4], and the sensors on the leg (15 to 18) are fixed with heat gear tights WCM3693 made by Under Armour.

The result for sensor wearability is shown in Table 4. Sensors on the torso for aerobic training, sensors on the head for weight training, and sensors on the lower part of body for yoga poses showed low wearability.

[2]Dumbbell trainings are selected in reference to ExRx.net Exercise Prescription, http://exrx.net/Lists/Directory.html

[3]Yoga poses are selected in reference to Japan Yoga Meditation Association (in Japanese), http://www.yoga.jp/

[4]Under Armour, http://www.underarmour.com/

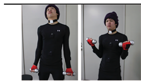
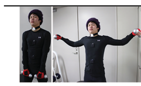
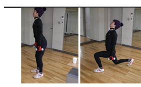
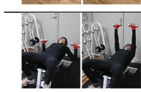
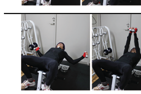
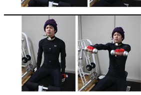
Illustration	Name
	Arm curl
	Front raise
	Shoulder press
	Lateral raise
	Shrug
	Rear lunge
	Front lunge
	Bench press
	Fly
	Arnold press
	Seated front raise

Table 2: Weight training.

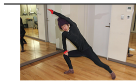
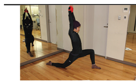
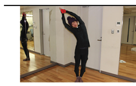
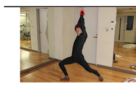
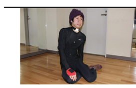
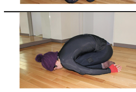
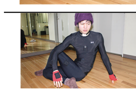
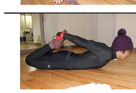
Illustration	Name
	Tree pose
	Extended triangle pose
	Extended side angle pose
	Crescent moon pose
	Crescent moon pose 2
	Warrior I Pose
	Sage twist
	Child's pose
	Half lord of the fishes pose
	Frog pose
	Corpse pose
	Bridge Pose

Table 3: Yoga poses.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Aerobic	A	A	A	B	A	A	A	A	A	A	B	C	C	C	A	A	A	A	A	A
Weight	B	B	C	A	A	A	A	A	A	A	A	A	A	C	C	A	A	A	A	A
Yoga	A	C	C	A	A	A	A	A	B	B	A	A	C	C	A	A	C	C	C	C

Table 4: Sensor wearability.

A simple way to decide sensor placement considering its wearability is not to use sensors whose wearability is low. However, sensor whose wearability is low may be discriminative and contribute to the recognition accuracy. Suppose using three sensors on unobstructed position or one sensor on obstructed position whose performance are equivalent, selecting configuration would depends on the users. Therefore, in this paper, we define an evaluation equation to obtain scores considering recognition accuracy and sensor wearability.

Questionnaire survey for trade-off between accuracy and wearability

We conducted a questionnaire survey for trade-off between accuracy and wearability. The following three questionnaires were sent out for twenty males and two females.

Q1. How many percentage of improvement in accuracy do you expect by attaching one extra sensor? Regardless of loading position.

Q2. Assuming that you are attaching several sensors over the body each of which has three degrees of wearability. A: a sensor on arm when doing sit-up. B: a sensor on the chest when doing back-extension, C: a sensor on the back when doing sit-up.

   a. Suppose you can detach one sensor whose wearability is "C" by attaching sensors whose wearability is "B" instead. How many sensors of "B" do you attach? Recognition accuracy does not change.

b. Suppose you can detach one sensor whose wearability is "B" by attaching sensors whose wearability is "A" instead. How many sensors of "A" do you attach? Recognition accuracy does not change.

Table 5 shows results of the questionnaire. From the result, we define an evaluation function of sensor placement considering accuracy and wearability, then find the best sensor placement meeting the recognition accuracy that user requires.

Answerer	Q1 [%]	Q2(a)	Q2(b)
1	2	10	5
2	5	10	5
3	2	5	3
4	3	2	2
5	4	10	10
6	2	5	3
7	5	4	2
8	5	5	5
9	3	3	3
10	5	20	15
11	5	20	20
12	4	3	3
13	5	5	3
14	4	3	2
15	3	7	5
16	2	5	3
17	3	3	3
18	4	4	2
19	5	3	2
20	5	10	10
21	3	10	3
22	5	3	2
Average	3.82	6.82	5.05

Table 5: Results of questionnaire.

Evaluation function

The expectation of improvement in accuracy by attaching a sensor of "A", "B", and "C", which is to say trade-off, is measured from the results of the questionnaire. The average of result for Q1 is 3.82 %, which is an expectation of improvement in accuracy for attaching one sensor. The average of results for Q2(a) and (b) are 6.82 and 5.05, which means the number of sensors whose wearability is "B" and "C" corresponding to one sensor whose wearability is "A".

From these results, we define the evaluation equation of sensor combination as follows:

$$S = P - (a + b \times 5.05 + c \times 6.82) \times 3.82, \qquad (1)$$

where S is the score of combination of sensors used, P is recognition accuracy with the sensor combination, a, b, c is the number of sensors whose wearability is "A", "B", and "C", respectively. Calculating the score for each sensor combination, appropriate sensor configuration considering the trade-off between accuracy and wearability can be shown to the user if the user set the requirement of the tolerance of accuracy.

Evaluation

Setup

Data ware captured from two male subjects and two female subjects aged twenties, who attached twenty 3-axis wireless accelerometers on their body same as in Figure 1. They acted seven aerobic training, nine weight training using dumbbell, and twelve yoga poses.

The accelerometers used have Bluetooth connectivity, however, one host computer can connect to seven client sensors at most. We used three laptop PCs: SONY VGN-SZ84PS (Core2Duo 2.20 GHz CPU, 1.5 GB memory), SONY VGN-UX90S (Genuine Intel U1400 1.20 GHz CPU, 504 MB memory), and Lenovo X220i (Core i3-2310M 2.10 GHz CPU, 4.00 GB memory). The sampling frequency was 100 Hz. Each activity was conducted for 10 seconds. Training was conducted in a training studio.

Recognition algorithm
Generally, using an activity recognition algorithm, raw data would not be used but preprocessed for extracting the feature values to grasp the meaning of sensed data. Supposing time $t = T$ now, the algorithm uses mean $\mu_i(T)$ and variance $\sigma_i^2(T)$ for 60-dimensional (20 sensors $\times$ 3 axes) sensed data $x_i(T)$ $(i = 1, \cdots, 60)$ over 100 samples retraced from time $t = T$.

$$\mu_i(T) = \frac{1}{100} \sum_{t=T-99}^{T} x_i(t) \tag{2}$$

$$\sigma_i^2(T) = \frac{1}{100} \sum_{t=T-99}^{T} \{x_i(t) - \mu_i(T)\}^2 \tag{3}$$

Feature vector $Z(T)$ is normalized using the following equation for 120-dimensional vector $F(T) = [\mu_1(T), \cdots, \mu_{60}(T), \sigma_1^2(T), \cdots, \sigma_{60}^2(T)]$, where M and S are the mean and the standard deviation of F, respectively.

$$Z(T) = \frac{F(T) - M}{S} \tag{4}$$

After this conversion, the mean and variance of $Z(T)$ become 0 and 1, respectively.

The logged data in the experiment were manually labeled, 20 sample of which becomes training data and the remaining data is used for testing.

The test data are recognized by calculating distance to all the training data. Label of training data whose distance is the smallest of all is output as a recognition result. We adopt Euclidean distance

$$d_i = \sqrt{\sum_{j \in mounted} (z_i - z_j)^2}. \tag{5}$$

Results considering recognition accuracy only
In an actual use, there exist the users who require higher accuracy using many sensors and who require moderate accuracy using few sensors. A simple way to control the trade-off between accuracy and the number of sensor is to set a tolerance of accuracy. Setting the tolerance of accuracy, the best sensor combination is one with the smallest number of sensors whose lowest accuracy of all the activities the highest and surpasses the tolerance of accuracy.

Table 6 shows the sensor combination chosen by selecting the fewest number of sensors whose accuracy is the highest satisfying the tolerance of accuracy. For example, setting the tolerance to 90%, the accuracies must not be lower than 90% for all the activities. " mark in the table shows that sensor combination does not change as the tolerance is reduced. - mark shows that there is no sensor combination meeting the tolerance even if all the sensors are used. In an actual use in this case, the user is asked to reduce the tolerance till the combination is found. For the results, setting high tolerance, the number of sensors used increases. The selected sensor combination includes sensors on the back and lower part of the body, while these sensors have been assessed as low wearability for aerobic training, weight training and yoga poses.

	Sensor(s) used and (lowest accuracy)			
Tolerance of accuracy	Aerobic training	Weight training	Yoga poses	All training
100%	3,7 (100%)	-	16 (100%)	-
99%	"	14,16,17,18 (99.15%)	"	14,18 (99.19%)
98%	16 (98.55%)	"	"	"
97%	"	"	"	"
96%	"	"	"	15 (96.04%)
95%	"	"	"	"
94%	"	14,16,18 (94.85%)	"	"
93%	"	"	"	"
92%	"	"	"	"
91%	"	"	"	"
90%	"	"	"	"
89%	"	"	"	"
88%	"	"	"	"
87%	"	"	"	"
86%	"	"	"	"
85%	"	8,15 (85.55%)	"	"

Table 6: Sensor placement that meets tolerance of accuracy.

Results considering recognition accuracy and sensor wearability
The results obtained in the previous section showed the sensor combinations considering recognition accuracy only, therefore some result combinations would be annoying. We find the sensor combinations considering both recognition accuracy and sensor wearability.

Firstly, we find the combinations where lowest accuracy of all the activities is not lower than the tolerance and wearability for all sensors are "A". Then select the combination where the number of sensors is the fewest and the recognition accuracy is the highest.

For the results shown in Table 7, there is no sensor combinations meeting more than 90% of tolerance for weight training and more than 86% of tolerance for all training. This is because sensors that performs well were not chosen due to low wearability. Seeing in detail, 89% of accuracy for weight training is achieved with three sensors without considering wearability (Table 6), while same accuracy is achieved with four sensors with considering wearability (Table 7).

	Sensor(s) used and (lowest accuracy)			
Tolerance of accuracy	Aerobic training	Weight training	Yoga poses	All training
100%	7,15 (100%)	-	16 (100%)	-
99%	16 (99.66%)	-	"	-
98%	"	-	"	-
97%	"	-	"	-
96%	"	-	"	-
95%	"	-	"	-
94%	"	-	"	-
93%	"	-	"	-
92%	"	-	"	-
91%	"	-	"	-
90%	"	-	"	-
89%	"	8,10,11,12 (89.25%)	"	-
88%	"	"	"	-
87%	"	8,11,15 (87.80%)	"	-
86%	"	"	"	-
85%	"	8,15 (85.55%)	"	8,15 (85,55%)

Table 7: Sensor placement that meets both tolerance of accuracy and sensor wearability.

Results considering a score of evaluation function
Though the results in the previous section did not use sensors whose wearability is "B" and "C", some users may

accept low-wearability sensors for higher degree of accuracy. Table 8 shows the sensor combinations that gives the highest score obtained from our evaluation equation that meet the tolerance of accuracy. Higher degree of score means that wearability of the sensor combination is better, and the score increases as the tolerance of accuracy decreases, which means that wearability improved by giving up recognition accuracy.

No sensor combination was found whose accuracy is more than 86% for all training when considering hard-wearability in the previous section, while sensor combination is found in such cases by using our evaluation function even though low-wearability sensors are used.

Conclusion

We proposed an evaluation function that evaluates sensor combination considering recognition accuracy and sensor wearability. We experimentally investigated the wearability of sensor placement attaching twenty sensors over the body and the recognition accuracy for thirty kinds of activities including aerobic training, weight training, and yoga poses. Wearability is defined by the degree of discomfort while doing training. From the questionnaire survey, we have defined an evaluation function and found the sensor combination based on the score of the function. We have confirmed that the evaluation function finds the sensor combination whose wearability is the best with meeting the tolerance of accuracy that user indicated.

However, very small sensors may be released in the future. Although the results reported in this paper would change in that case, our evaluation function can be used by changing the parameters through questionnaire survey. As a future work, we plant to make an evaluation function taking fashionability into consideration.

	Sensor(s) used, (lowest accuracy), and [score]			
Tolerance of accuracy	Aerobic training	Weight training	Yoga poses	All training
100%	7,15 (100%) [92.36]	-	16 (100%) [96.18]	-
99%	"	14,16,17,18 (99.15%) [61.66]	"	14,16,17,18 (99.15%) [17.23]
98%	16 (98.55%) [94.73]	"	"	"
97%	"	"	"	"
96%	"	"	"	14,15,16,19 (96.75%) [37.05]
95%	"	"	"	"
94%	"	"	"	14,16,18 (91.45%) [57.58]
93%	"	"	"	"
92%	"	"	"	"
91%	"	"	"	14,15,16 (91.45%) [57.78]
90%	"	"	"	"
89%	"	8,10,11,12,15 (89.95%) [70.86]	"	"
88%	"	8,11,12,15 (88.40%) [73.13]	"	"
87%	"	8,11,15 (87.80%) [76.35]	"	"
86%	"	"	"	"
85%	"	8,15 (85.55%) [77.91]	"	8,15 (85,55%) [77.91]

Table 8: Sensor placement that meets tolerance of accuracy and evaluation function score

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