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Users Viewing Exhibit Similarity-based Contents Recommendation Service by Activity Recognition

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Abstract

We developed a user's viewing path similarity-based contents recommendation algorithm using LBS (Location Based Services). However, the previous research had a problem that it might recommend contents related with exhibits which users did not like because it divides an exhibition into the areas and recommends contents based on them. To solve this problem, we propose the service based on activity recognition using 3-axis accelerometer sensor. In this service, it is determined by analysis of user's movements that the corresponding user is moving or viewing. Also, it measures the viewing time that the user spent on viewing exhibits and determines user's location using LBS. It might recommend more suitable contents to the user's taste because it focuses on the exhibits which users actually watch long.

Keywords: *Activity recognition, Location awareness, Viewing time, 3-axis accelerometer sensor*

1. Introduction

Activity recognition has gained a lot of interest in recent years due to its potential and usefulness for context-aware computing such as aged care monitoring [1] and smart homes [2]. Basically, the purpose of activity recognition is to infer people's behaviors from low-level data acquired through sensors in a given setting, based on which other critical decisions are made. For instance, in smart home environments for aged care monitoring [2], based on the information provided by cameras and other pervasive sensors, the system needs to automatically monitor the occupant and determine when they need assistance, raising an alarm if required.

With recent advance in sensor technologies, the sensors which are collecting information of users' movement and surrounding areas are developed [3]. The sensors are mounted on the smart phone. As the smart phones are more widely useful, the various location-based services, such as indoor directions, shopping guides, advertising and parking guidance, are available in the mobile environment. In addition, the studies providing the services and recognizing the various actions of users are starting to emerge.

In this paper, we present a user's viewing exhibit similarity-based contents recommendation service by activity recognition. This service recognizes the action which user does in a museum using 3-axis accelerometer sensor. Also, it measures the viewing

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time of exhibit during “viewing” phase. It recommends contents using information of user`s activity and viewing time. It might recommend more suitable contents to the user's taste because it focuses on the exhibits which users watch actually long.

The rest of the paper is organized as follows. Section 2 reviews related works and section 3 and 4 introduce a user’s activity recognition and location tracking service using 3-Axis accelerometer sensor and LBS and a user’s viewing exhibit similarity-based contents recommendation service by activity recognition. In sections 5, we verify superiority of our proposed service mechanism against the previous one and conclude this paper.

2. Related Work

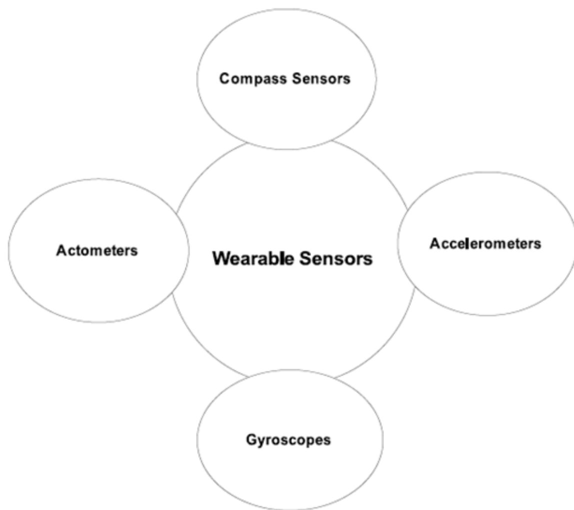


Figure 1. Different wearable sensors used to capture and analyze human movement

A range of wearable sensors, shown in Figure 1, have been used to assess daily mobility levels in free-living subjects. Of these, accelerometers have emerged as the most useful tool for mobility assessment in both clinical and home environments. The reasons for such a wide acceptance of accelerometers are: Firstly, they can respond to both frequency and intensity of movement. This fact makes them superior to actometers or pedometers which are attenuated by impact or tilt [4]. Secondly, most of the widely available accelerometers can measure both the movement and the tilt which makes them superior to motion sensors that lack the capabilities of measuring these characteristics. Thirdly, due to enhancements in microelectromechanical systems (MEMS) technology, today’s accelerometers are not only coming in small size and at a low-price but are also capable of demonstrating a high degree of reliability in measurement.

Most physical activity recognition systems have used accelerometers which are capable of responding to acceleration due to gravity as well as acceleration due to movement. At any point in time, the output of such accelerometers is a linear combination of these two components, the acceleration component due to gravity (GA) and the acceleration component due to bodily motion (BA) [5]. Since these two components are linearly combined and overlap both in time and frequency, they cannot be easily separated. However, low pass filtering can be used to make approximation to the two components. Low pass filtering, when applied to an acceleration signal, separates the GA from the actual signal. GA can then be subtracted from the original signal to obtain the BA. Since most human movements occur between 0.3 and 3.5 Hz [6], most investigators have used a filter with a cut off frequency between 0.1 and 0.5 Hz to separate the two components.

Accelerometers are devices which are capable of measuring the applied acceleration acting along a sensitive axis [4]. Accelerometers use transducers for measuring acceleration. These come in different varieties, such as piezoelectric crystals, piezoresistive sensors, servo force balance transducers, electronic piezoelectric sensors and variable capacitance accelerometers. Some accelerometers require an external power supply whereas others do not. Moreover, some accelerometers are capable of responding to static accelerations (such as the acceleration due to gravity) whereas others do not.

Figure 2. Sensor-specific 3D coordinate systems

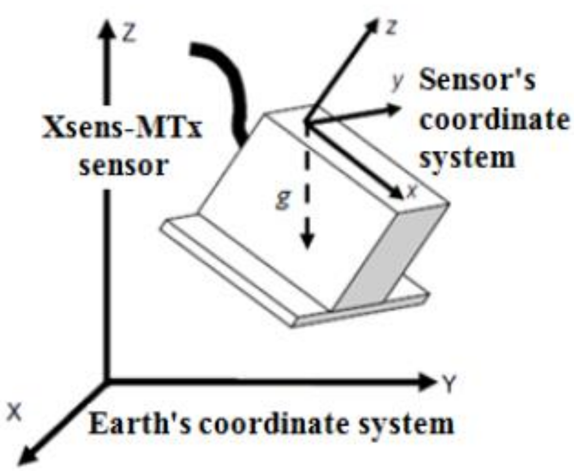
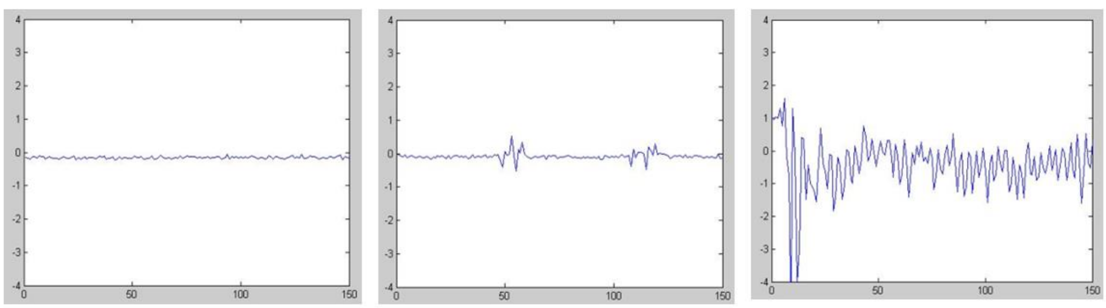


Figure 3. Earth-specific and sensor-specific 3D coordinate systems, and the Earth's gravity

A 3-axis accelerometer is a sensor that returns a real valued estimate of the acceleration along the axes x, y and z. It measures the acceleration and output the projections of the acceleration vector represented in a 3D coordinate system. In Figure 2 an accelerometer with its coordinate system is presented. Because of the Earth's gravity, all objects experience a gravitational pull towards the Earth's centre. When the accelerometer is at rest, the only force that is affecting the sensor is the Earth's gravity. The acceleration unit of the pull is referred to as g or g-force. Consequently all objects are subject to 1 g acceleration. Figure 3 shows the accelerometer with its coordinate system and the g-force that is influencing it. This information about the g-force is of great interest to us. Using the gravity component we can find out the orientation of the sensor (*e.g.*, vertical, horizontal), which enables us to distinguish between different activities (*e.g.*, standing, lying).

The measured acceleration vector is directed upwards (positive value for the z axis), even though the gravitational force pulls downwards. That means that only when the accelerometer is in free fall it will measure a value of zero. Even though its speed is increasing, it is in an inertial frame of reference, in which it is weightless. When the accelerometer is at rest, it will measure 1 g upwards. The accelerometer is not measuring gravity, but the force of the surface on the body that counteracts gravity.

3. Activity recognition using 3-axis accelerometer sensor



(a) Viewing (b) Viewing(small movements) (c) Movement

Figure 4. Filtered data from 3-axis accelerometer sensor

In this section, we propose the activity recognition method using 3-axis accelerometer sensor. The action which user does in a museum is the two, viewing and movement. So, the proposed method recognizes just one of them.

The proposed method is as follows. It filters the data received from 3-axis accelerometer sensor. And it compares the data with the critical value to distinguish the users' activity. If the data exceed the critical value more frequently with 70% during a regular period, it decides "movement". If it is not, it decides "viewing". It measures the viewing time of exhibit during "viewing" phase. Figure 4 shows the data received from 3-axis accelerometer sensor are filtered by the service.

To find a viewing exhibit, the proposed method uses the information of LBS and activity recognition. If the data shows that there is no users' movement during a certain period of time, the service measures the users' location using the Wifi signal map collected in advance [7, 8]. It finds the exhibit which user views and measures a viewing time using the information of LBS and activity recognition.

4. Users viewing exhibit similarity-based contents recommendation service using LBS

In this section, we propose the contents recommendation service based on viewing path and activity recognition. The proposed service consists of three phase. First, by using the activity recognition method, it extracts the exhibits which user watched. Second, it measures the similarity by comparing the extracted exhibits with exhibits which the other users watched. Finally, it calculates a contents preference. The preference applies the weighted value of primary about the entire contents and in proportion to watching time. And it applies the weighted value of the contents related with exhibits watched by the other users having the similarity, which are more than 70% comparing the user with them. The service recommends the contents to the user by the preference.

Figure 5 shows the pseudo-code extracting the viewing exhibit of the user.

```
extractViewingExhibit(User)
{
   int vn = 0;
   for(int i=0; i<Exhibit.Count; i++)
   {
      if(User. Exhibit[i].ViewingTime > Exhibit[i].avgViewingTime)
      {
         User.ViewingExhibit[vn++] = Exhibit[i];
      }
   }
   return User.ViewingExhibit;
}
```

Figure 5. Extracting the viewing exhibit of the user.

In Figure 5, *Exhibit.Count* represents the total number of the exhibit and *User.Exhibit[i].ViewingTime* represents the viewing time when *User* watched the exhibit *i*. *Exhibit[i].avgViewingTime* represents the average viewing time of the exhibit *i*. *User.ViewingExhibit* represents the viewing exhibit of *User*.

The similarity between users about watched exhibit can be measured as equation (1).

$$sim_{ViewingExhibit}(u,pu) = \frac{n(VE_u \cap VE_{pu})}{n(VE_u)} \tag{1}$$

In the Equation (1), the argument *u* presents current user and *pu* presents previously user who has completed a tour. VE_u presents the viewing exhibit of user *u* and VE_{pu} presents the viewing exhibit of previously user *pu*. $n(VE_u)$ presents function that find the number of elements of set VE_u and $n(VE_u \cap VE_{pu})$ presents function that find the number of elements of the intersection of VE_u and VE_{pu}.

Figure 6 shows the pseudo-code to obtain the contents preference.

```
ContentsPreference()
{
   for(int i=0;i<Contents.Count;i++)
   {
      for(int j=0; j<preUser.Count; j++)
      {
         if(simViewingExhibit(User,preUser[j])>0.7)
         {
            for(int e=0; e< preUser.VE.Count; e++)
            {
               if(contents[i] ∈ preUser[j].VE[e].Contents)
               {
                  contents[i].weight  =
                  simViewingExhibit(User,preUser[j])  *  contents[i].weight
                  + contents[i].weight;
               }
            }
         }
      }
   }
}
```

Figure 6. Calculating the contents preference.

In Figure 6, *preUser.Count* represents the total number of previously users. *preUser[j]* represents previously user *j*. *simViewingExhibit(User,preUser[j])* represents the viewing exhibit similarity between *User* and *preUser[j]*. *preUser[j].VE[p].Contents* represents the list of contents in the viewing exhibit of *preUser[j]*. *contents[i].weight* represents the weighted value of contents *i*. If the contents *i* is in *preUser[j].VE[p].Contents*, *contents[i].weight* is adjusted by *simViewingExhibit(User,preUser[j]).*

It recommends the contents which it is right for a taste to user through the adjusted weight value.

The threshold defines 0.7, meaning very strong relation by Pearson correlation coefficient because the users having the similarity more than the specific value can be seen to have the similar tastes [9].

5. Performance Evaluation

In this section, we can show how effectively the proposed service can recommend visitors their favorite contents and solve the problems of existing service. Our experimental environment is in Table 1.

Table 1. Experimental environment

Parameter	Value
No. of Exhibition Rooms	10
No. of Area	30
No. of Exhibits	60
No. of Contents	60
No. of Previous Visitors	100

We assume that the number of exhibition rooms is ten and each room has three areas. So, there are a total of 30 areas. Each area has two exhibits. So, there are a total of 60 exhibits. Each exhibit has one related contents. So, the total number of contents is 60. The number of previous visitors is 100. We assume that previous visitors watch at least three exhibitions, stay at least five areas, and watch long at least five exhibits.

In order to evaluate the proposed method, we set up three users. The first user has watched rooms 1, 2, 6, 7 and 9 and stayed at area 2, 3, 17, 18 and 27 and watched long at exhibit 2, 8, 31, 35 and 53. His or her favorite contents would be 2, 8, 31, 35 and 53. The second user has watched rooms 2, 3, 6, 7 and 10 and stayed at area 4, 9, 17, 20 and 28 and watched long at exhibit 7, 14, 34, 38 and 50. His or her favorite contents would be 7, 14, 34, 38 and 50. The last user has watched rooms 1, 3, 5, 8 and 9 and stayed at area 3, 7, 14, 24 and 25 and watched long at exhibit 5, 16, 30, 48 and 50. His or her favorite contents would be 5, 16, 30, 48 and 50.

Experiments are performed to find out how the preference values for the present user are changed depending on which services are applied, that is, users similarity method based on tagging patterns [10] and proposed method. Additionally, we can find out how many differences occur between these services to contents based on the user preference.

Table 2. Contents Preference Ranking of User A

Ranking	Tag		Activity	
	Contents No.	Contents Preference	Contents No.	Contents Preference
1	5	4.4	2	2.05
2	34	4	53	2.05
3	35	3.9	5	1.95
4	36	3.9	1	1.8
5	53	3.9	16	1.7
6	54	3.9	8	1.65
7	14	3.8	35	1.65
8	1	3.65	9	1.55
9	2	3.65	33	1.55
10	50	3.65	34	1.55

In the first experiment, Table 2 is a list of content preferences of top 10. In the case of Tag, the user`s favorite contents in the Top 10 is three. In the case of Activity, the user`s favorite contents in the Top 10 is four.

Table 3. Contents Preference Ranking of User B

Ranking	Tag		Activity	
	Contents No.	Contents Preference	Contents No.	Contents Preference
1	14	4.85	34	2.05
2	5	4.3	16	1.95
3	17	4.3	33	1.8
4	13	4.05	5	1.7
5	34	4	14	1.65
6	42	3.95	9	1.55
7	18	3.9	15	1.55
8	1	3.8	42	1.55
9	2	3.8	50	1.55
10	49	3.8	56	1.4

In the second experiment, Table 3 is a list of content preferences of top 10. In the case of Tag, the user`s favorite contents in the Top 10 is two. In the case of Activity, the user`s favorite contents in the Top 10 is three.

Table 4. Contents Preference Ranking of User C

Ranking	Tag		Activity	
	Contents No.	Contents Preference	Contents No.	Contents Preference
1	14	5.1	5	2.45
2	5	4.8	16	2.45
3	13	4.3	30	2.05
4	49	4.3	48	2.05
5	50	4.3	50	2.05
6	1	4.05	15	1.8
7	2	4.05	49	1.8
8	17	4.05	1	1.55
9	53	4.05	2	1.55
10	54	4.05	45	1.55

In the third experiment, Table 4 is a list of content preferences of top 10. In the case of Tag, the user`s favorite contents in the Top 10 is two. In the case of Activity, the user`s favorite contents in the Top 10 is five.

In the experiments, the proposed service has the low preference compared to other services because the number of other users watching similar exhibits is small. The low preference doesn`t have a meaning because the service recommends the contents based on the relatively preference to users.

6. Conclusions

In this paper, we present the contents recommendation service based on activity recognition that analyzes the user`s action using 3-axis accelerometer sensor and recommends the contents by the analyzed information. The propose service tracks the user`s location using 3-axis accelerometer sensor and LBS. It determines that user is moving or viewing by analysis of users movements using the information of 3-axis accelerometer sensor. Also, it measures the viewing time by analyzing the information of 3-axis accelerometer sensor and LBS. It might recommend more suitable contents to the user's taste because it focuses on the exhibits which users watch actually long. Through experiments, it shows that the proposed service effectively recommends contents that fit the user's taste.

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