IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727,
PP 22-25
www.iosrjournals.org

Improve Energy-Efficient Real-time Human Mobility State Classification Using Smartphone.

Pooja D. Andhale[1], Chaitali R. Kakad[2], Madhuri P. Lokhande[3] Nikhil V. Kapade[4]
[1,2,3,4,]*(Computer Engineering Dept., KVNNIEER NASHIK, India)*

Abstract: *The advantage of using the embedded accelerometer of smartphone for human mobility analysis, with or without location tracking based upon GPS, Wi-Fi is that it is energy-efficient and has high availability. Using an accelerometer for human mobility analysis has its challenges as carrying our smartphones differently as well as the measurements are body placement dependent. And it often relies on an on-demand remote data exchange for processing; which is less energy-efficient and is not real-time. We're presenting a framework based upon an algorithm that reduces the effect of different smartphone on-body placements as well as orientations and allows human movements to be accurately and energy efficiently identified. Focusing the only use of embedded smartphone accelerometer without referencing previous data and accelerometer noise filtering, this method can identify the human mobility state.*

Keywords: *Energy efficiency, embedded system, real-time system, human mobility classification.*

I. Introduction

A. Problem definition

In this rapidly progressing locality everyday *n* number of mobile devices are flooding in market which is exhaustingly utilizing multiple remote services via wireless medium in order to keep the device user on tract. Location mapping or Location Based Service (LBS) is one such exhaustively utilized service which is consumed by multiple devices to locate its position on the terrain and displacement from point to point.Transceiver based location signal sensors such as GPS and some based upon Wi-Fi, require data exchange between multiple transmitters and receivers. These require an active transceiver link that can be affected by different kinds of electromagnetic interference and signal variation that lead to position inaccuracies of the order of 10m and in turn lead to inaccuracies in the derived velocity and acceleration.

B. Relevant theory:

Mobility Based Services (MBS), in contrast to Location Based Services (LBS) focus on mobility in the sense of someone or something moving in the physical world to a targeted destination. The emphasis is on the type of th e movement or mobility rather than on the position or location context, however these two can be combined in a complementary manner. At a high level abstraction, mobility represents human mobility type of activity such as stationary versus walking, e.g., stationary for some time at a location such as a restaurant at lunchtime can indicate someone is on a lunch break. Different patterns of mobility can be used to determine the transportation mode of the user, such as, the user is in a moving vehicle versus walking etc. The AAMPL, i.e., Accelerometer augmented mobile phone localization detects a user's movement using the phone's accelerometer and places the mobile phone in the right context. The AAMPL framework augments the approximate physical location of a mobile phone with a context-aware logical localization. Energy Efficient Mobile Sensing System (EEMSS) uses the embedded mobile phone sensor to identify human mobility states. The combination of sensor used such as readings from an accelerometer, Wi-Fi, GPS, and a microphone to auto-recognize the human mobility state defined in three dimensions: 1]motion (such as running or walking), 2]location (such as staying at home or in a motorized vehicle on a freeway) 3]background environment (such as a loud or quie t location).

II. Literature Survey

The accelerometer which is embedded in a Smartphone is the most valuable non -transceiver based sensor. The embedded sensor provides the data for activity monitoring as it gives more information about human movements. Hence, our main focus is on using only the Smartphone accelerometer for human mobility state classification.The non-transceiver based sensor, i.e., accelerometer has three main advantages over transceiver based location signal sensors. 1] It consumes low energy of 96 mW as compared to 330 mW and

1426 mW by GPS and Wi-Fi scans respectively. 2] No delay while starting the accelerometer; however GPS takes time as receiving location update depends on a start mode. In a hot start mode the Termed -Time-to Subsequent-Fix (TTSF) is about 10 seconds and in a cold start mode the Time-To-First-Fix (TTFF) could take up to 15 minutes. 3] The non - transceiver based sensor, i.e., accelerometer readings are continuously available as compared to transceiver based sensors that can be affected by obstructions and faulty transceiver links.

Classification of human mobility activity using Smartphone is challenging as it includes, *1] the readings and* measurements of accelerometer for human mobility are body position dependent, and it is impractical that to have a fixed body placement in real-world activity classification. *2]* the issue of accelerometer noise. There are two main noise sources, the mechanical thermal and electrical thermal noise. To achieve high level of classification accuracy a low-noise measurement system is useful a. *3]* the issue of energy-efficiency. This due to limited resources in Smartphone. Using transceiver based location sensors such as GPS or Wi-Fi requires continuous location updates and this can exhaust the Smartphone battery within 12 and 46 h ours respectively. But in the Android, sensing mode for non-transceiver based sensors such as accelerometer the Smartphone can be exhausted in approximately 4hr only.

III. System Design

A .System Architecture

The design of embedded real-time systems has several requirements and constraints which includes cost, limited resources, performance of control algorithms and energy consumption. Fig. 1 shows the EHMS architecture. The EHMS is Energy-Efficient Human Mobility Sensing. The accelerometer is a one kind of key sensor which minimizes user interaction in ubiquitous computing. Readings from an embedded Smartphone accelerometer are used to determine the human mobility state. The orientation readings from magnetometer are ignored because of large errors caused in the presence of metals. Hence, measurements of magnetic flux tend to show distortion for trains, buses and cars. Here, we are not using a compass because there is no need to get the direction.

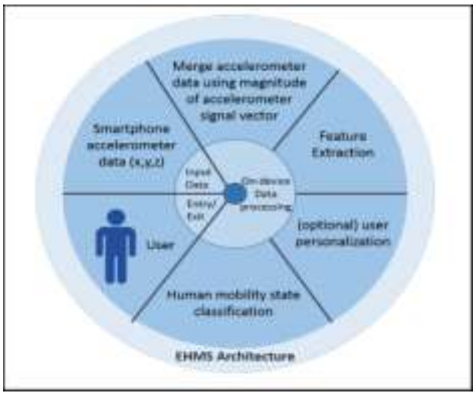

Fig. 1 : EHMS Architecture

B. Human Mobility State Classification:

As we found different human mobility states such as stationary vs. walking could be classified using peak and trough. And there are also some similar activities such as jogging vs. walking may overlap in result so, to calculate them there are features like mm, Pmm and Tmm.

1) Peak (P):

$$Qi=\begin{cases}1, & (\ +1<\ )\\ 0, & (\ \ +2>\ +1)\ h\end{cases}$$

$$P=\sum_{=0}^{-2}(Qi)$$

Where, Xi is the v of each accelerometer data point.
n is the total number of data points.
P is the total numbers of peaks.

2) Trough (T):

$$Qi=\begin{cases}1, & (\ +1<\ )\\ 0, & (\ \ +2>\ +1)\ h\end{cases}$$

$$T=\sum_{=0}^{-2}(Qi)$$

Where, Xi is the v of each accelerometer data point
n is the total number of data points.
T is the total numbers of troughs.

3) Tpt: The sum of the total number of peak (P) and trough (T) acceleration values.

Tpt= P+T.

B. **User Personalization**

There is possibility that different human mobility patterns generated by user are for similar activity, e.g. what is classified as jogging for some group might be classified as walking for another. So, we are personalizing EHMS framework by the algorithm based on the accelerometer data gathered for particular activity. The algo rithm is reconfigured for the user personalization. The algorithm uses Tpt range estimation, Pmm & Tmm range calculations.

1] Pmm range calculation**:** This is the range between the minimum and maximum peak values given the T_{PT} range for the activity. The Pmm is useful in distinguishing between subtle human mobility states such as travel by underground train vs. bus or car.

2] TPT range estimation**:** The range where the corresponding sum of the Gaussian distribution for 2 or 3 consecutive T_{PT} values is ≥ 75%. The 75% threshold was chosen based on the analysis of accelerometer data gathered from 15 volunteers. Given the Gaussian distribution of T_{PT}, if the sum of distribution percentage for 2 or 3 consecutive T_{PT} values is ≥ 75% then the T_{PT} range is between the corresponding minimum and maximu m T_{PT} values.

```
Algorithm 1: Pmm range pseudo code

Require: A = {xi.....xn} // Peak values i = 0, n = 6.
Require: SA = size (A)   // array size of A.
Ensure: E= Φ, i =0, k = 0
    For all υ in {A0; A1, . . .A(SA-1)} do
        Ek=∑_{i=k}^{k+1} υi //sum of two consecutive elements in E
        k=i
  end for
   ME = max (E)
   if ME ≥75 then
        minp = min(ME,ME+1)
        maxp =max(ME,ME+1)
   return (minp , maxp) // pmm
  else
   reset(E)  //reset to an empty set
        for all υ in {A0, A1, . . .A(SA-2)} do
         Ek=∑_{i=k}^{k+2} υi //sum of three consecutive elements in E
        k=i
   end for
   ME =max(E)
   if ME ≥75 then
        minp = min(ME,ME+1,ME+2)
         maxp =max(ME,ME+1,ME+2)
        return (minp, maxp) // pmm
   end if
end if
```

```
Algorithm 2: TPT range estimation pseudo code

Require: A ={xi.....xn }  // Peak values. i =0; n = 6.
Require: SA = size(A)    // array size of A.
Ensure: E= Φ ; i =0; k = 0
      for all  υ in {A0, A1, . . .A(SA-1)} do
         Ek=∑_{i=k}^{k+1} υi   //sum of two consecutive elements in E
          k=i
   end for
    ME = max(E)
    if ME ≥75 then
    return index (ME,ME+1) // return index of the max
                           // E and end of the next element.
   else
    reset(E)  //reset to an empty set
          for all υ in {A0, A1,. . .A(SA-2)} do
             Ek=∑_{i=k}^{k+2} υi //sum of three consecutive elements in
E
          k=i
    end for
    ME =max(E)
    if ME ≥75 then
          return index (ME,ME+1,ME+2)
    end if
```

IV. Application

Project focused mainly on Android based phones, EHMS can be used with any type of smartphone.

1) Determine the human mobility state based upon the readings from accelerometer, e.g., trigger a pedestrian map after detecting walking and shows nearby places if user ask for.
2) If determined activity is motorized then a map focuses more on main road routes.
3) If user wish to know about calorie count then provides the calorie burnt chart based on user profile.

V. Result Analysis

The first screen is opening screen when user will tap on application EHMS screen will appear. On clicking START button the application will start working in background that means accelerometer will start collecting readings. As the application is working in background so it will keep collecting readings unless and until user click on STOP. After clicking on STOP, the accelerometer will stop collecting readings.

Picture 2: Start/Stop Screen   Picture 3: M enu & Statistics

The EHMS menu contains different contents like 'Home', 'History', 'Statistics' and so on. If user wants to check his calorie count then click on statistics that will show the 'calorie burnt' graph to user.

VI. Conclusion

Position based sensors alone can't differentiate between human transport modalities, e.g., GPS cannot classify between cycling and traveling using a slow moving bus or car in a congested traffic. We can combine acceleration data with location determination, this will add some more human mobility context.

Combining acceleration and location determination will also provide more accuracy in terms of time constraint. The method EHMS, classifies human mobility states using a probabilistic algorithm and feature extraction on the smartphone accelerometer data. The method can within 2 seconds (8 accelerometer samples) classify activities with a high accuracy.

VII. Future Scope

There is a wide scope for features related to health. And maintain detail health record with respect to user profile. The user profile with respective to male and female, as their calorie count, walking, exercising etc. differs.

Acknowledgements

We would like to thank our project coordinator and project guide Prof. N.V. Kapade (Computer Dept.) for guiding us so well. We would also like to thank our Head of Department Prof. K. V. Ugale (Computer Dept.) for providing resources we needed. And would also thank to our team for supporting and working hard.

References

[1]. I. Constandache, S. Gaonkar, M. Sayler, R. R. Choudhury, and L. Cox,"EnLoc: Energy -efficient localization for mobile phones," in Proc. 28th IEEE Int. Conf. Comput. Commun., 2009, pp. 2716–2720.

[2]. L. Bao, and S. S. Intille, "Activity recognition from user-annotated acceleration data," in Proc. 2nd Int Conf. Pervasive Comput., 2004, pp. 1–17.

[3]. A. Ofstad, E. Nicholas, R. Szcodronski, and R. R. Choudhury, "AAMPL: Accelerometer aug mented mobile phone localization," in Proc. 1st Int. Conf. Mobile Entity Localization Tracking GPS-Less Envir., 2008, pp. 13–18.