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HUMAN ACTIVITY RECOGNITION BY TRILITERATION HMSA

Yogesh Kumar M[1]
Student, M.E (Computer Science Engineering),
MKCE, Karur, Tamilnadu, India,
Yogesh301991@gmail.com

Sindhanai Selvan K[2]
Senior Asst proff, M.E (Computer Science Engineering), MKCE,
Karur, Tamilnadu, India, sindhanai@gmail.com

***Abstract*— Elegant strategy such as Smartphone application able to give the functions of a pedometer by the accelerometer. To attain a high correctness the devices contain to be damaged on specific on-body location such as on an armband or in footwear. Usually public carry elegant devices such as Smartphone in different positions, thus making it not practical to use these devices due to the abridged correctness. Using the implanted Smartphone accelerometer in a low-power mode there an algorithm named Energy-efficient Real-time Smartphone Pedometer which accurately and energy-efficiently infers the concurrent person step count within 2 seconds with the Smartphone accelerometer. Technique involves take out 5 features from the Smartphone 3D accelerometer devoid of the need for noise filtering or exact Smartphone on-body placement and compass reading; Energy-efficient Real-time Smartphone Pedometer categorization correctness is around 94% when validated using information collected from 17 volunteers.**

Keywords— Pedometer, Accelerometer, Smartphone, Activity categorization

1.Introduction

Smart phones provide sophisticated real-time sensor information for dispensation. Researchers contain studied a large number of sensors such as accelerometer, gyroscope, rotation vector, and direction sensors in person step count projects. Of these the accelerometer is the majority precious non-transceiver sensor used to give the information for activity monitoring as it gives more information concerning movement armed forces. Therefore the core center of this system is on using solely the smart phone accelerometer for person pace count. The accelerometer has three input advantages over transceiver based place signal sensors such as GPS. First, low energy spending of 60 mW. Second, there is no wait when starting the accelerometer, however receiving position updates in GPS depends on the start mode. In a hot start form the Termed-Time-to-Subsequent-Fix is about 10 seconds and in a cold create mode the Time To-First-Fix could take up to 15 minutes. Third, sensors interpretation are incessantly available with the accelerometer as compare to GPS and Wi-Fi which could be thwarted as of signals transmit by GPS satellites and being out of range of Wi-Fi signals in that order. Person movement categorization using smart phones requires a movement condition gratitude technique that can function regardless of the position of the smart phone because placing accelerometers on exact parts of the body makes it not practical for use in the real-world. Acceleration information differs for similar behavior, thus making it harder to finely secernate between certain types of activity. Limits have been found in the range of movement activities identified by use of an only one sensor and; due to the complexity of person movement and noise of sensor signal, action categorization algorithms tend to be probabilistic. They have in its place designed a various modal sensor panel that concurrently captures information from many sensors. A major challenge in the design of ubiquitous, context-aware smart phone applications is the increase of algorithms that can find the person action using noisy and equivocal sensor information. There a technique called Energy-efficient Real-time Smart phone Pedometer; an Android based smart phone application to accurately calculate person steps. The novelty of this investigate as compared to existing systems are: ERSP extracts five features this scheme works an energy-efficient frivolous arithmetical model to process in real-time the activity accelerometer information with no need for noise filtering and works in spite of of the smart phone on-body placement and orientation.

2. Related work

Takamasa Higuchi, Hirozumi Yamaguchi, and Teruo Higashino proposed a novel social navigation framework, called PCN that leads users to their friends in a crowd of neighbors. PCN provides relative positions of surrounding people based on sensor readings and Bluetooth RSS, both of which can be easily obtained via off-the-shelf mobile phones. Through a field experiment in a real trade fair, demonstrated that PCN improves positioning accuracy by 31% correction mechanism. Furthermore, showed that the geometrical clusters in the estimated positions are highly consistent with actual activity groups, which would compared to a conventional approach owing to its context-supported error help users to easily identify actual nearby people.

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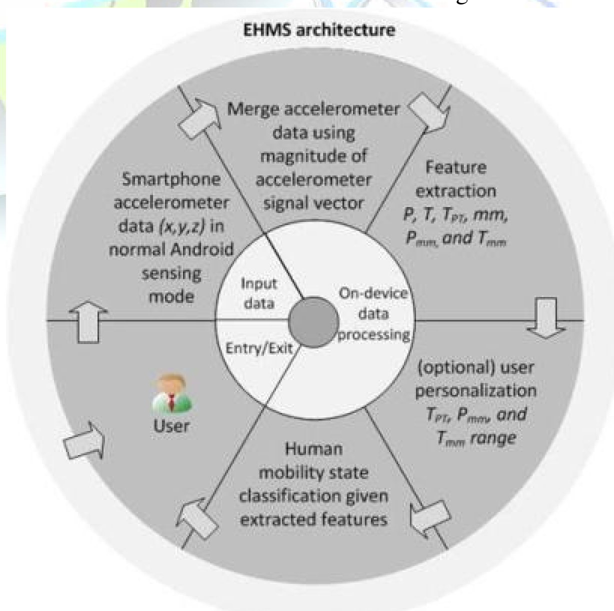
TABLE 1
Summary of Factors Affecting Human Mobility Profiling Using Smartphones

Reference	Number of subjects	Human mobility states	Frequency	Sensors used	Mobility state classifiers	Smartphone placements	Real-time, time constraint (secs)
Ofstad et al. [12]	1	Stand, sit	1Hz	Accelerometer, GPS	Raw data	Right trouser pocket	Yes, Non-constant
Reddy et al. [15]	16	Still, walk, run, bike, metro	1-3Hz	Accelerometer, GPS	Variance, DFT	free, arm, bag, chest, hand, pocket, waist	No, N/A
Wang, Chen et al. [18]	7	Stand, walk, cycle, bus, car, under-ground train	35Hz	Accelerometer	Mean, standard deviation, mean crossing rate, third-quartile, sum and standard deviation of frequency com-ponents	Free	No, N/A
Khan et al. [7]	6	Stand, walk, run, cycle, car	45Hz	Accelerometer	coefficient, magni-tude, linear-dis-criminant, kernel-discriminant	Front and trouser pockets	No, N/A
Wang, Lin et al. [19]	10	Still, run, walk, vehicle	Unknown	Accelerometer, GPS, micro-phone, Wi-Fi scan	Standard deviation	Free	Yes, 6
Kjaergaard et al. [8]	Unknown	Stand still, move	30Hz	Accelerometer, GPS	Variance	Free, jacket pocket	Yes, 1
Hache et al. [6]	5	Stand, walk, sit, lying down	50Hz	Accelerometer	Standard deviation	pelvis	No, N/A
Nick et al. [11]	5	Car, train, pedestrian	38Hz	Accelerometer	Standard devia-tion, max value, norm, number of	Bag, trouser, pocket, palm	No, N/A

Emiliano miluzzo, nicholas d. Lane, kristof fodor, ronald peterson,mirco musolesi, shane b. Eisenman, xiao heng, hong lu, andrew t. Campbell proposed the execution, evaluation, and user experiences of the CenceMe request, which represents one of the primary application to without human in tervention get back and issue sensing attendance to common networks by Nokia N95mobile phones. Described a complete system execution of CenceMe with its presentation assessment. Discussed a number of significant design decisions wanted to resolve various limitations that are there when annoying to deploy an always-on sensing request on a profitable mobile phone. Also obtainable the results from a long-lived experiment where CenceMe was used by 22 users for a three week period. Discussed the user study and lessons learn from the deployment of the request and tinted how might get better the application moving forward.

Jialiu Lin Yi Wang,Murali Annavaram, Quinn A. Jacobson,Jason Hong,Bhaskar Krishnamachari,Norman Sadeh, Presented the design, execution, and evaluation of an Energy Efficient Mobile Sensing System (EEMSS). The center part of EEMSS is a sensor organization scheme for mobile devices that operates sensors continuously, by selectively turning on the minimum set of sensors to monitor user state and triggers new rest of sensors if necessary to achieve state transition findion. Energy consumption can be reduced by shutting down needless sensors at any particular time. Implementation of EEMSS was on Nokia N95 devices that use sensor management scheme to



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deal with built-in sensors on the N95, including GPS, Wi-Fi find or accelerometer and microphone in order to achieve person daily activity recognition. Also proposed and implemented novel categorization algorithms for accelerometer and microphone calculations that work in real- instance and lead to good performance. Finally, we evaluated EEMSS with 10 users from dual universities and were able to provide a high level of accuracy for state recognition, acceptable state transition findion latency, as well as more than 75% gain on device lifetime compared to existing system.

TABLE 2
Participants, Activities, and Smartphone On-Body Placements for Which Accelerometer Data Was Gathered

Participant	Activities	On-body placements
User 1, 2, 3, 4, 5, 6, 7	Sitting, standing, walking, and jogging.	N/A
User 8, 9, 10, 11	Travel by underground train and light rail train, car, bus, cycling, and taxi.	N/A
User 12, 13	Stationary and lying down.	N/A
User 14, 15	Walking.	Top-jacket pocket, front trouser pocket, backpack, and palm

Donnie H. Kim, Jeffrey Hightower, Ramesh Govindan, Deborah Estrin proposed a Place Sense provides a significant improvement in the aptitude to find out and be familiar with places. Precision and recall with Place Sense are 89% and 92% versus the previous state-of-the-art Beacon Print approach at 82% and 65% precision and recall. Because it uses response rate to select representative beacons and suppresses the influence of infrequent beacons, Place Senses accuracy gains are particularly noticeable in challenging radio environments where beacons are inconsistent and coarse. Place Sense also finds position entry and exit times with over twice the accuracy of previous approach thanks to sensible use of buffering and timing. It has the aptitude to overlap the exit fingerprint of one place with the entrance fingerprint of the following position. Lastly, position Sense is accurate at discovering places visited for short durations or places where the device remains mobile. correctness in short-duration and passing places is a important payment since these types of places are valuable to promising applications like life-logging and social position sharing.

Ionut Constandache, Romit Roy Choudhury,Injong Rhee, proposed the growing status of location based services calls for better quality of localization, counting greater ubiquity, correctness, and energy-efficiency. Present localization schemes, although efficient in their target environments, may not level to meet the evolving needs. This system proposes CompAcc, a easy and sensible method of localization via phone compasses and accelerometers. CompAcc's core idea has been branded for centuries, yet, its adoption to person scale localization is not obvious

3.Algorithms

Movement categorization algorithms

Acceleration information also varies for similar activities, thus making it extra difficult to finely differentiate certain type's activity. A major dispute in the design of ubiquitous, context-aware smart phone application is the expansion algorithms that can find the person movement state using noisy and equivocal sensor information. Limits have been found in the range of movement activities recognized by use of single sensor mainly and; due to the difficulty of person movement and noise of sensor signals, movement categorization algorithms tend to be probabilistic.

Accelerometer based algorithm

This algorithm works an energy-efficient light-weight exact model to process in real-time the movement accelerometer information without the need for noise filtering and it mechanism in spite of the smart phone on-body assignment and compass reading. In terms of person movement analysis, our accelerometer based algorithm can be used separately or as part of mixture structural design, e.g., it can be used in a joint accelerometer and location strength of several mind approach.

Different person movement patterns tend to be generated algorithms

The algorithm have to be able to adapt to the various variation as a user is performing an activity, e.g., what is classified as walking for a sure group might be confidential as jogging for another group. The first step involves personalizing EHMS by reconfiguring the algorithm depend on the smart phone accelerometer data extract for the exact activity. To personalize the application based on a specific action, the user performs the activity for a one-off time of 14 seconds. Fourteen seconds was chosen because a limit of 56 accelerometer samples are essential to cover the T range from 0 to 6.

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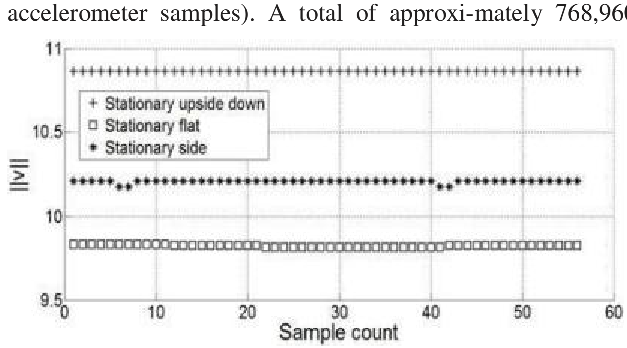
3.4 Accelerometer Noise Filtering

The Kalman filter outstanding the algorithm's aptitude to efficiently computes accurate estimate of the true value given noisy capacity. The accelerometer readings give sensibly precise information for movement finding, and for this reason the Kalman filter algorithm is well matched for altering the Gaussian process and to aid in real-time person movement state calculation. Also there is no need to keep historical measurements and estimates as only the present and self- assurance estimate levels are required**.**

4.Energy-efficient human mobility sensing

The design of embedded real-time systems has several requirements and constraints, including limited resources, cost, performance of control algorithms, and energy con-sumption [5]. Fig. 1 shows the EHMS architecture. The accelerometer is a key sensor to minimize user interaction in ubiquitous computing and to determine the human mobility state we use the readings from an embedded smartphone accelerometer. We ignore the magnetometer which provides orientation readings because of large errors caused in the presence of ferrous metals. Hence, magnetic flux measurements tend to show strong distortions for trains, buses and cars [23]. The combined use of electronic compasses and accelerometers creates a directional trail of the user [21].

We have been able to accurately classify accelerometer data from a specialized subset of human mobility states including stationary with no movement e.g., smartphone resting on a table, stationary with slight movements (sitting, lying down, and standing) and in-motion (walking, jogging, cycling, motorized movement including travel by bus, light rail train, underground train, taxi, and car). We grouped the 12 activities and focused on nine similar human mobility states, e.g., travel by bus is grouped as being similar to travel by car. It should be noted that we are not classifying high speed trains as we focused on shorter commuter trips within urban city locations. The location context may also be ambiguous, e.g., bus-stops may also coincide with traffic impediments such as traffic lights or road junctions. Also for motorized movement we considered only non-station-ary movements. Our pattern recognition model was tested against the smartphone accelerometer data gathered from 15 adult able-bodied individuals for a minimum of 360 sec-onds (1,440 accelerometer samples). A total of approxi-mately 768,960



seconds (3,075,840 accelerometer samples) was obtained. There were a total of six females and nine males. Six were between the age of 20 and 30, four were between the age of 30 and 40, three were between the age of 40 and 50, and two were older than 60. EHMS consists of two aspects. They are the human mobility state classifica-tion and the optional user personalisation.

Human Mobility State Classification

Using the embedded smartphone accelerometer we are able to detect patterns based on the vertical ðyÞ axis. The vertical axis presented the most differences because of the orienta-tion of the device during the experiments. The case is the reverse for accelerometer data gathered for similar activities with different smartphone on-body placements. In such cases, more than one axis needs to be taken into consider-ation for a pattern match to be found. To combine ðx; y; zÞ readings regardless of the smartphone orientation we make use of the magnitude of the accelerometer signal vector (MASV). Given the accelerometer The following light-weight computation features are extracted as classifiers from the accelerometer readings for a given human mobility state. One of our aims for selecting features is to only select those features that are

Fig 2 Support Vector Machine

simple but effective. A simple feature refers to a feature that is compu-tationally light to calculate (e.g.,time domain features) and can be extracted using a comparatively low sampling rate such as 4 Hz used in this paper.

We studied the impact of different smartphone orienta-tions and on-body placements on human mobility data gen-erated by EHMS with two commercial human step count Android applications. The applications are Runtastic[1] and Accupedo.[2] We calculated the accuracy for 10 human steps while walking with the smartphone placed in the four pre-viously identified on-body positions. Table 3 shows details of the comparison. The results show the human step count accuracy of EHMS was slightly inflated when the smart-phone was placed in the

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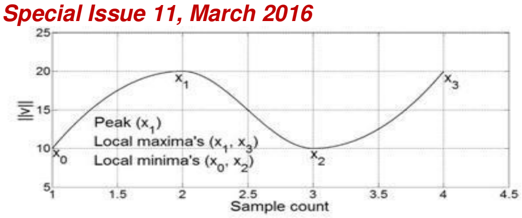
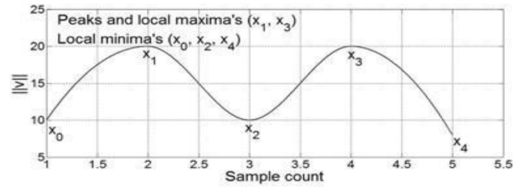
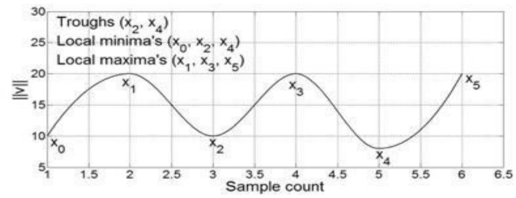


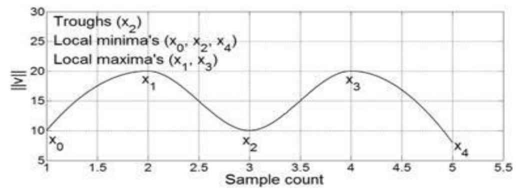
(a) Peak and local maxima count differ because the first and last elements are not local minima's.



(b) Peak and local maxima count are the same because the first and last elements are local minima's.



(c) Trough and local minima count differ because the first element isn't a local maxima.



(d) Trough and local minima count differ because the first and last elements are local minima's.

backpack. The additional steps were mainly recorded during the transfer of the smartphone to and from the backpack. This was a similar case for the front trouser pocket. The human step count accuracy for carrying the smartphone in the palm and top-jacket pocket positions was unaffected regardless of the smartphone ori-entation and on-body placement.

56 accelerometer samples are required to cover the T range from 0 to 6.

Energy-Efficiency

This is achieved by sampling power hungry transceiver

1689

TABLE 3
Results from 10 Human Steps over Two Iterations Using the Step Count Applications

Application	Palm	Front trouser pocket	Backpack	Top jacket pocket
Runtastic	(3,5)	(13,12)	(15,14)	(9,11)
Accupedo	(11,12)	(18,21)	(26,22)	(14,15)
EHMS	(10,10)	(12,10)	(11,11)	(10,11)

TABLE 4
CPU and RAM Utilized per Activity

Activity	CPU% range	Average CPU%	RAM (Mb) range	Average RAM (Mb)	Process package
Browsing	(9,90)	45.4	(45.2,76.4)	60.5	com.android.browser
Camera	(23,42)	31.2	(13.8,14.6)	14.2	com.android.camera
Game	(13,24)	19.6	(13.3, 13.9)	13.5	com.htc.android.teeter
Active call	(2,13)	8.16	(25.4,26)	25.8	com.android.phone
Music	(0,2)	2	(12.8,21.4)	19.1	com.htc.music
EHMS	(0,2)	1	(3,3.2)	3.1	com.ooshin.ehms

These features were selected based on our study of the jjvjj wave patterns gener-ated for different activities.We find the peak and trough (see the following sections) better characterizes the wave patterns than the standard local/global maxima/minima. EHMS to conduct real-time human mobility state classification. reconfiguring the algorithm based on the smart phone accelerometer information gathered for the exact activity. To personalize the application based on a specific action, the user performs the activity for a one-off time of 14 seconds. Fourteen seconds was chosen because a minimum of

sensors such as GPS based on the human mobility state. Table 5 shows the battery utilization results of the accelerometer vs. GPS. The accelerometer tests were done for the four Android sensing modes: normal, ui, game and fastest. The results were obtained by extracting the smartphone battery statistics from full battery charge until exhausted using the Battery Manager API provided by the Android Software Development Kit. Furthermore the smartphone screen lights were turned-on for the duration of some of the accelerometer tests. This was necessary to sample the accelerometer data continuously in background mode. It took approximately the same amount of time to exhaust the smartphone battery with continuous GPS loca-tion sampling as compared to combined GPS and acceler-

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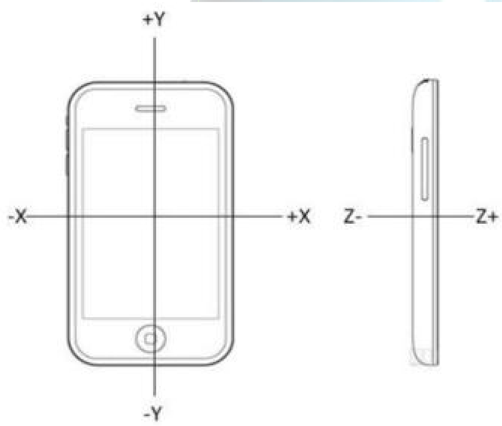
ometer in normal sensing mode. In the Android OS, the amount of energy consumed when sampling the accelerom- eter in normal mode is negligible as long as the screen is lit or the CPU is running. This is because this mode is already being used continuously to detect tilting of the mobile device for use in different applications [16]. The energy-efficiency experiments were conducted using a Samsung Galaxy II running Android version 4.0.4 with a 1500 mAh standard battery capacity. To be energy-efficient, EHMS is based on the embedded smartphone accelerometer running in normal sensing mode.

As seen in the analysis above using only the $T_{P\ T}$ distribu-tion we can classify activities such as walking with a classifi-cation accuracy of 98 percent, but is insufficient at classifying activities such as travel by light rail train versus underground train. Research by [15] studied features such as range, mean, standard deviation, and correlation of the jjvjj. Even though these features presented differences in activities there were issues with overlapping results. This indicates that these features are ineffective in classifying activities.

5.Results

For optimum classification accuracy, a comparatively low sampling frequency of 4 Hz is used by EHMS and the win-dow size for feature extraction is 2 seconds. If the frequency isn't 4 Hz then EHMS still uses eight accelerometer samples per cycle for classification, but will misclassify activities since the window size is no longer 2 seconds.



(a) Smartphone accelerometer (x, y, z) coordinates.

(b) Upward vertical orientation.

(c) Side orientation.

(d) Downward vertical orientation.

(e) Flat horizontal orientation.

The Kalman filter is a parametric model that can be applied to both stationary and in-motion human mobility data analysis [24]. We investigated whether or not a discrete Kalman filter algorithm could filter the accelerometer noise thus The accelerome-ter readings provide reasonably accurate data for mobility detection, and for this reason the Kalman filter algorithm is well suited for filtering the Gaussian process and to aid in real-time human mobility state prediction. Also there is no need to retain historical measurements and estimates as only the current and confidence estimate levels are required. An optimal comparative model was used for the evalua-tion. For J48 the confidence factor used is 0.25, the minimum number of instances is 2, and 10-fold cross-validation. The 10-fold cross-validation is required for two reasons. First, the construction of the decision tree can be affected by a high variation in the accelerometer data, second to avoid over fitting thus leading to a poor accuracy. Once a model was obtained for each classifier we used 600 instances for predictions with unknown samples We combine accelerometer readings by calculating the magnitude of the accelerometer signal vector z_k. We opted to apply Kalman filter directly to z_k rather than on vector ð$w^x{}_k$; $w^y{}_k$; $w^z{}_k$Þ because depending on the smartphone place-ment as the acceleration vector increases in a specific direc-tion, the associated accelerometer readings grow larger along the affected axis and could be constant along the rest.

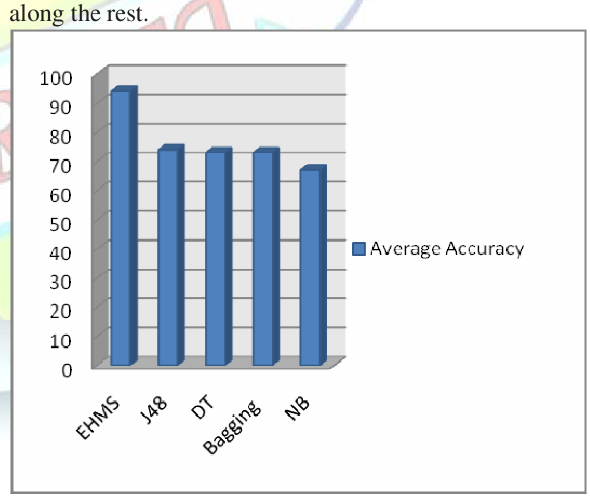


Fig.2 EHMS vs. known existing classifiers

3D Accelerometer Model

The 3D accelerometer measurement is modelled as follows [7]:

z_k ¼ a_k g_k þ b_k þ $v_{A;k}$; (9)

z_k is the sensor readings at time k; a_k is the acceleration, g_k is the gravity, b_k is the offset, and $v_{A;k}$ is the observed noise. z_k is a vector in the 3D Cartesian coordinate system as followed:

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We opted specific direc-tion, the associated accelerometer readings could be constantalong the rest. We applied the Kalman filter on 1,250 samples of gathered accelerometer data for the following activities: walking, sta-tionary, and driving. Due to the accelerometer noise the fil-ter caused historical measurements to have adverse effects on estimates. To overcome this issue of a corrupted filter, rather than applying the Kalman filter continuously we reset the filter every accelerometer eight samples. This ensures in case of errors that only one user activity calcula-tion is affected. Based on different on-body placements we found Kalman filtering not useful in classifying activity states. Even though the noise was filtered the required computational features were stymied in the output. For this reason EHMS doesn't perform any accelerometer noise filtering because the required features were no longer retrievable on the body placement of the human. Evaluated EHMS using existing classifiers. The classifiers are J48, decision table (DT), bagging, and naive bayes. Fig. shows the precision and remembers contrast of EHMS vs. known existing classifiers with and without personalization. Trained the classifiers using an information set comprised of pre-classified accelerometer information for the following activities: light rail train, car, jogging, lying down, stationary and walking. To obtain a model for the classifiers, the classifiers were trained using the same set of 1,250 accelerometer samples for every action with a 10 fold cross-validation. From the unprocessed information the same feature, extracted intended for categorization. Contrast with other existing classifier EHMS is makes the better accuracy it shown in below chart.

6. Conclusion

Concurrent person movement state categorization algorithm without need for referencing historical information. Categorization of the person movement state regardless of the smart phone position and on-body placement. The proposed representation is comparatively insensitive to noisy information. Found even though the noise was reduced when Kalman filtering was applied, the computational features were stymied in the output making it use superfluous in classifying between different person movement conditions. Light-weight accelerometer information feature extraction. EHMS extracts five novel features counting one derived feature from the accelerometer information. Further there is no need for a remote server link for computational purposes as all processing is performed inside the smart phone. More energy-efficiency due to the small computational algorithms and smart phone implanted accelerometer sensing mode at four samples per instant.

Although, we focused mainly on Android based phones, we envisage that EHMS can be used with any type of smart-phone as the micro-electro-mechanical systems (MEMS) specification is similar across a range of smartphones.

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