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# HUMAN ACTIVITY RECOGNITION BY TRILITERATION HMSA

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***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**

## I. 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 motivation for MBS, in contrast to LBS, includes:

1. Adapting dynamically the types of mobility information services based upon the travel mode, e.g., a pedestrian map triggered after detecting walking, shows safer places to cross roads whereas a motorist map focuses more on main road routes.
2. Mobility profile driven social and societal behaviour analysis changes via gamification and incentives, e.g., to promote greater low carbon transportation modes and low-energy transport usage.
3. Real-time human mobility profiling, such as determining the degree of physical exercise, the usage patterns for types of public and private transport, lowcarbon transport usage and the time spent at a location (This latter aspect can indirectly indicate human activities even personal preferences at that location e.g., spending more time near one shop location rather another one can indicate shopping and a greater user preference or interest for one shop as compared to another.
4. Human activity driven system control and optimization, e.g., switching off power hungry location sensors such as the GPS receiver and Wi-Fi when out of range, i.e., when travelling in an underground train.

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.

## II. 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% compared to a conventional approach owing to its context-supported error correction mechanism. Furthermore, showed that the geometrical clusters in the estimated positions are highly consistent with actual activity groups, which would help users to easily identify actual nearby people.

**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 intervention 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, QuinnA.Jacobson, JasonHong,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 hierarchically, by selectively turning on the minimum set of sensors to monitor user state and triggers new set of sensors if necessary to achieve state transition findion. Energy consumption can be reduced by shutting down unnecessary sensors at any particular time. Implementation of EEMSS was on Nokia N95 devices that use sensor management scheme to manage 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 readings that work in real-time and lead to good performance. Finally, we evaluated EEMSS with 10 users from two 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

**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 emerging applications like life-logging and social location 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 scale to meet the evolving needs. This system proposes CompAcc, a easy and sensible method of localization using phone compasses and accelerometers. CompAcc's core idea has been known for centuries, yet, its adoption to person scale localization is not obvious

## III. ALGORITHMS

### 3.1 MOVEMENT CATEGORIZATION ALGORITHMS

Acceleration information also varies for similar activities, thus making it extra difficult to finely differentiate certain type's activity. A major challenge in the design of ubiquitous, context-aware smart phone applications is the growth 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.

### 3.2. 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 works regardless of the smart phone on-body placement and compass reading. This method adapts the standard Support Vector Machine (SVM) and exploits fixed-point arithmetic for computational cost reduction. 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 mind approach.

### 3.3. 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 based on the smart phone accelerometer information gathered for the exact activity. A comparison with the traditional SVM shows a significant improvement in terms of computational costs while maintaining similar accuracy, which can contribute to develop more sustainable systems for Ambient Intelligence. 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 56 accelerometer samples are required to cover the T range from 0 to 6.


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 findion, and for this cause the Kalman filter algorithm is well suited for filtering the Gaussian process and to aid in real-time person movement state calculation. Also there is no need to retain historical measurements and estimates as only the present and self-assurance estimate levels are required. From the unprocessed information the same feature, extracted intended for categorization. It takes less memory. To personalize the application based on a specific action, the user performs the activity for a one-off time of 14 seconds.

## IV. RESULTS

The experiments conducted involved the study of accelerometer data gathered from various activities. The key objective of the scientific experiment is to investigate features such as peaks and troughs that can be extracted from the accelerometer readings to classify similar human mobility states such as travel by light rail train vs. underground train. The data collection process was conducted by 15 participants for 12 different activities. In order to validate EHMS we required a wide range of realistic user data to stress test the algorithm. The activities were selected because they were amongst the most popular types of modality and offered a wide range of normal urban commuting activities. Table 2 shows the activities recorded by each user. EHMS uses aggregated classes for user activity classification, e.g., although users 12 and 13 only performed two activities, their samples are classified using the aggregated class (which has all 12 types of activities). Users 1 to 13 were permitted to carry the smartphone regardless of the on-body placement. Users 14 and 15 had to place the smartphone in predetermined body positions. This allowed us to study the differences in accelerometer readings based upon different smartphone on-body placements and orientations. For each activity we used 1,250 training data points. This is equivalent to 312.5 seconds per activity. We chose 1,250 samples because the data gathering process required each participant to perform an activity for a minimum of 360 seconds. It should be noted that we found 14 seconds (56 samples) was sufficiently long to personalize the EHMS Android application for a specific user activity. In this paper real world data was gathered using Android based smartphones. No accelerometer data noise filtering or data simulation was used. In several cases even similar activities cannot be grouped together, e.g., it can be argued that different kinds of low and high speed over ground trains will generate different human mobility profiles. We selected a small subset of human mobility states for demonstration purposes since EHMS can be dynamically applied to a wide range of human mobility states. 4.1 Accelerometer Noise Filtering For optimum classification accuracy, a comparatively low sampling frequency of 4 Hz is used by EHMS and the window 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. 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 ameliorating the activity state detection accuracy estimation. We chose to use the Kalman filter due the algorithm's ability to efficiently compute accurate estimates of the true value given noisy measurements. The accelerometer 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.

## V. ANALYSIS

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.

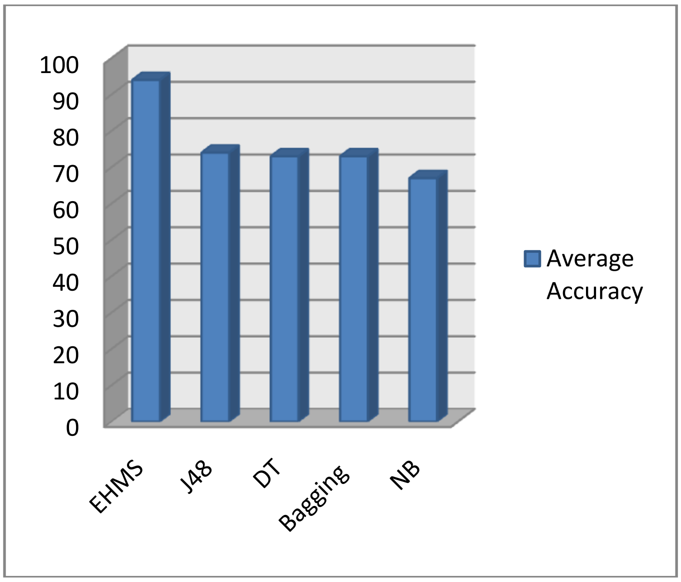


Fig.1 EHMS vs. known existing classifiers

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. It takes less memory. Contrast with other existing classifier EHMS is makes the better accuracy it shown in below chart.

## VI. 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.

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