A Single vs. Multi-Sensor Approach to Enhanced Detection of Smartphone Placement

John J. Guiry, Chris J Karr, Pepijn van de Ven, John Nelson, Mark Begale

Abstract— **In this paper, the authors evaluate the ability to detect on-body device placement of smartphones. A feasibility study is undertaken with N=5 participants to identify nine key locations, including in the hand, thigh and backpack, using a multitude of commonly available smartphone sensors. Sensors examined include the accelerometer, magnetometer, gyroscope, pressure and light sensors. Each sensor is examined independently, to identify the potential contributions it can offer, before a fused approach, using all sensors is adopted. A total of 139 features are generated from these sensors, and used to train five machine learning algorithms, i.e. C4.5, CART, Naïve Bayes, Multilayer Perceptrons, and Support Vector Machines. Ten-fold cross validation is used to validate these models, achieving classification results as high as 99%.**

Keywords: Smartphone Placement, Multi-Sensor Fusion, Enhanced Contextual Awareness, Machine Learning

I. INTRODUCTION

The smartphone is finding itself ever more useful in mHealth applications. Extensive research has already taken place to generate machine learning models to detect the physical and emotional wellbeing of smartphone users e.g. [1]–[3] . These models often assume a single on-body device location, e.g. pants pocket [4]–[7]. However, variations in on-body device placement can have significant implications for machine learning models, particularly when those models assume a single on-body location [8].

One of the major differences between a smartphone and dedicated device is on-body location. Dedicated devices often stipulate a fixed on-body location for correct usage. For example, the ActivPAL[9] requires the use of PALstickies to retain the dedicated physical activity monitor to a participant's thigh. However, such stringent on-body device placement is unappealing with a smartphone.

Research conducted by Ichikawa *et al.* [10] on 419 subjects across three countries suggests that 34% of respondents keep their phone in a trouser pocket, while 33% keep a phone in their handbag. A further 8% used a backpack, while just 6% of respondents placed their phone in upper body pockets. Detecting where the smartphone is located forms the core of this paper.

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AT Kearney [11] estimate that by the year 2017, OECD countries will save $400 billion from yearly healthcare costs, due to adopted mobile health solutions. Such solutions may come in the form of smartphone based applications, designed to monitor physical activity, prevent and detect falls, and monitor gait in real-time. The role smartphones can play in these areas is immense, albeit impacted by variations in on-body device location.

Detecting device placement has advantages beyond user driven preventative healthcare. For instance, detecting that a phone is in a purse or handbag, an algorithm can automatically adjust the ringer volume, to ensure a higher likelihood of gaining the owner's attention. Similarly, modern smartphones come with increasingly sophisticated yet power hungry hardware, particularly the on-board processor. Pre-emptively lowering the CPU clock frequency when the device is detected in a pocket or handbag will likely have no effect on perceived performance, while improving battery life.

Section II presents related work in this area, while section III presents the design considerations taken into account during the study. Section IV provides details of the feasibility study. Section V briefly describes the signal processing required before feature generation can occur. A description of the features generated is presented in section VI. Results attained using five *de-facto* machine learning algorithms are presented in section VII, with a subsequent discussion in section VIII, before a conclusion is presented in section IX.

II. RELATED WORK

Yang *et al.* [12] have attempted to detect when a mobile phone is in any of three states: in a bag, pocket or out of pocket or bag. They do so using both light and proximity sensors on a Samsung Tizen device. However the proximity sensor found on the Tizen device operates differently from the majority of current commercial implementations, in that it will report an estimate of distance in centimetres from among eight different discrete levels. The majority of current phones in the marketplace will only report two discrete states from this sensor: near or far. Thus its use in a widespread implementation is difficult. The authors developed a demo application for the Tizen device, capable of inferring two placements: in pocket or out of pocket. During testing over several days, the authors claim accuracies of up to 98%.

Miluzzo *et al.* [13] attempted to infer if a phone is in a pocket or not, using both Gaussian Mixture and Support Vector Machine based models. The authors implemented a lightweight model using both a Nokia N95 and Apple iPhone. However, the only sensor used is the microphone. While this appears to have led to promising results, the authors point out that use of additional sensors, particularly the accelerometer, magnetometer and light sensors, would be quite useful. Again, trial data was collected from a single person transitioning through various environments for several hours.

III. Design Considerations

A. Device Selection

It was decided to use a Galaxy Nexus smartphone for data collection. The Nexus smartphone comes with a diverse range of sensors, including accelerometer, magnetometer, gyroscope, pressure, proximity, and light sensors.

B. Selected Sensors

For the purposes of this study, it was decided to use the accelerometer, magnetometer, gyroscope, pressure, and light sensors, all available on the Samsung Galaxy Nexus device. The accelerometer, magnetometer, and gyroscope were chosen as these can detect fine grained detail pertaining to motion. The pressure sensor was chosen as this may assist in differentiating on-body placement, particularly between locations at the thigh / hip, and locations closer to the upper torso, such as breast pocket. Finally, the light sensor was chosen as changes in the level of light detected may be evident between different locations.

C. Smart Device Limitations

It is necessary to accommodate for sporadic sampling on the device, which is an issue for all on-board sensors. On-board storage of 16GB for the Nexus will prove more than sufficient for the task at hand. Similarly, battery life is not of a concern here. Data can be gathered from the Nexus device over a 7-8 hour period, using the Purple Robot application[14]. These times are more than sufficient for scripted feasibility studies.

D. Smart Device Placement

As part of this study, it was decided to ask participants to place the smartphone in any of eleven separate on-body locations: back of belt, backpack, front of belt, left breast pocket, right breast pocket, left hip, right hip, left hand, right hand, left jeans pocket and finally, right jeans pocket. Participants did not typically use all eleven suggested locations during the trial. For instance, females partaking in the study typically did not wear clothing with pockets at the hip, and thus this location was not tested for these participants. The objective of the study was to gather data as realistically as possible.

IV. Feasibility Study

A feasibility study[1] with N=5 healthy young participants (2M, 3F), with a mean age of 26 years was undertaken to assess the characteristic signatures of each on-body location. Subjects were asked to walk a full running track multiple times. Phone placement was adjusted on each full loop of the track, to include either pants pocket, either jacket pocket, either hand, a back pocket and a backpack. Each loop of the track typically lasted about five minutes, though no explicit constraints were placed on participants.

V. Signal Processing

The accelerometer, magnetometer, and gyroscope were each interpolated to 100Hz. Similarly, the light and pressure sensors were interpolated to 10Hz. Bandpass filters are used for the accelerometer, magnetometer, and gyroscope with a lower and upper cut-off of 0.6Hz and 7.5Hz respectively. The light and pressure sensors are both low pass filtered at 0.1Hz, again to eliminate changes caused by frequencies outside of our interest.

A total of 50 annotated location segments were collected during this study. All segments were subsequently accepted for training or testing of the five machine learning models.

VI. Feature Generation

Features are generated during walking periods, using windowed sub-segments from the synchronised sensor signals. For the purposes of this research, a fixed window size of 2 seconds is used. The set of features generated can be found in Table I.

For the accelerometer, magnetometer and gyro signals, a template was constructed from eleven different possible phone locations: back of belt, backpack, front of belt, left breast pocket, right breast pocket, left hip, right hip, left hand, right hand, left jeans pocket and finally, right jeans pocket. Thus a total of 33 templates were generated, with each template lasting two seconds in duration. Correlation features are generated for each of these three sensors at every window. The template is compared to the incoming stream, and a correlation value is calculated from this on each two second interval. Characteristics from the signal can then be used, together with a number of additional features to distinguish between locations.

Similarly, activity counts are calculated from the tri-axial components of both accelerometer and magnetometer, together with root mean square values. The device angle is computed from the accelerometer and magnetometer. The peak power is calculated for all three sensors, together with peak frequencies. The primary frequency at which peak power occurs is also identified for all three sensors. Features are generated from the pressure sensor, including the altitude difference and average slope of the signal. Finally, features are generated from the light sensor to include mean lux, as an indicator of whether the phone is in a pocket or not.

Class labels were reduced from the original eleven locations to nine: the thigh, front of belt, hip, breast pocket, hand, backpack, back pocket, jacket pocket and handbag. These labels were used during model training and evaluation. In all 139 features were chosen for the fused model, 47 for the accelerometer, 46 for the magnetometer, 41 for the gyroscope, 3 for the light, and finally 2 for pressure.

[1] Study in collaboration with Northwestern University, Chicago, and ethically approved with reference number: 21825

TABLE I. FEATURE SET

Feature	Derived From*
Activity Counts x 6	A, M
RMS Counts x 2	A, M
Mean Uncorrected Device Angle x 2	A, M
Mean Corrected Device Angle x 1	A
Max Power x 9	A, G, M
Peak Frequency x 9	A, G, M
Peak Power x 3	A, G, M
Primary Frequency x 3	A, G, M
Altitude Difference x 1	P
Mean Slope x 1	P
Raw Mean Lux x 1	L
Low Pass Mean Lux x 1	L
Mean Differential Lux x 1	L
Peak Acceleration Correlation Coefficient x 33	A
Peak Gyroscope Correlation Coefficient x 33	G
Peak Magnetometer Correlation Coefficient x 33	M

*A = Accelerometer, M = Magnetometer, G = Gyro, P = Pressure, L = Light

VII. CLASSIFIERS

This section presents details on the dataset composition. Results are presented for on-body location classification using models generated from each sensor in isolation. A model is also generated using the fused approach comprised of accelerometer, magnetometer, gyroscope, pressure, and light sensors. The five classifiers considered are: C4.5, CART, Naïve Bayes, Multilayer Perceptrons and finally Support Vector Machines.

A. Dataset Composition

The original dataset consists of 50 segments, and represents 11,592 seconds worth of data (approximately 39 minutes per participant). A depiction of the unbalanced dataset can be found in Figure 1. Locations comprising of the thigh or hand account for 50% of the dataset. Thus, it was felt that balancing the dataset such that each location has an equal representation in the dataset would be useful. The balanced dataset contains 2070 instances, approximately a third of the size of the original unbalanced dataset. Results for both the balanced and unbalanced datasets are presented in the next section.

B. Classifying Location

Overall results attained using the balanced dataset can be found in Table II. From this table it can be seen that the accelerometer attains the highest average results, with an overall true positive rate of 96%. The fused approach attains similar results with average true positive rates at 92%. A particular discrepancy exists between the fused results and the sole accelerometer based results for the breast pocket location. In this case, a 15% difference in the number of correctly classified instances exists, with the fused approach confusing 18% of all breast pocket instances for in the hand. Some overlap existed in the amount of light detected between in the hand and breast pocket locations. Phone placement was noted as upright in the breast pocket, which meant that the light sensor (typically located at the top of a smartphone) detected a significant quantity of light in this

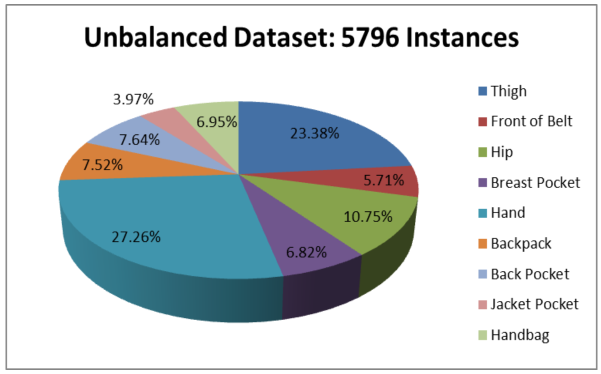

Fig 1. Dataset Composition (Unbalanced)

location. No other sensor confuses the breast pocket and hand locations to the same degree as the light sensor.

Results also demonstrate that the magnetometer and gyroscope can differentiate between locations, albeit with a lower success rate than either the accelerometer or fused approaches. Overall true positive rates for the magnetometer and gyroscope are 69% and 77% respectively. The hip has proven to be the most difficult location to infer for the magnetometer, with just 46% of all instances classified correctly. Many of these have instead been confused for the thigh (12.5%), breast pocket (11.7%), back pocket (9.5%) or front of belt (7.7%) locations. The back pocket has proven to be a difficult location for the gyro to infer, with an average of 61% of all instances correctly classified in this category. A further 19% of all instances are misclassified as either front of belt or hip locations. The light sensor does prove useful when differentiating the breast pocket and hand locations from all other locations, with average results attained of 77% and 74% respectively.

Finally, the pressure sensor has attained poor results for all nine locations. Average true positive rates for this classifier are just 13%.

Similar results are attained from the unbalanced dataset, though it is again noted that for sensors whose performance is poor for the task at hand (e.g. light and pressure sensors), misclassifications tend to be heavily biased towards both thigh and in the hand locations, which together accounted for approximately 50% of the unbalanced dataset. For the purpose of transparency, results attained using the unbalanced datasets are also provided in Table III.

Overall results for the accelerometer sensor are 96% for both balanced and unbalanced datasets, 4% and 2% higher than for the fused dataset respectively. In particular, the Support Vector Machine algorithm generated a better performing model for the accelerometer dataset than for the fused dataset, with balanced results of 99% and 77% respectively. Results for the gyro and magnetometer sensor also prove somewhat promising for location inference, with the average classifier correctly inferring 77% and 69% respectively. Both pressure and light sensors do not perform well, with results for the balanced dataset at 13% and 37% respectively.

TABLE II. BALANCED DATASET (2S WINDOW)

Classifier	Fused (%)	Acc (%)	Mag (%)	Gyro (%)	Press (%)	Light (%)
C4.5	97.77	98.93	74.34	77.29	14.15	50.00
CART	97.24	97.63	72.31	75.99	15.21	47.10
NB	91.78	89.80	54.10	74.63	13.57	30.28
SVM	77.68	99.08	76.03	75.55	14.54	29.61
MLP	98.16	97.10	71.49	82.36	11.11	30.38
Average	92.53	96.51	69.65	77.16	13.72	37.47

TABLE III. UNBALANCED DATASET (2S WINDOW)

Classifier	Fused (%)	Acc (%)	Mag (%)	Gyro (%)	Press (%)	Light (%)
C4.5	98.91	98.49	81.79	80.93	29.96	58.24
CART	98.46	97.48	81.84	80.57	29.57	58.48
NB	93.97	90.37	64.87	73.63	19.09	26.74
SVM	83.88	99.46	83.79	81.84	29.91	47.68
MLP	99.13	98.75	80.36	85.78	26.41	50.36
Average	94.87	96.91	78.53	80.55	26.99	48.30

VIII. DISCUSSION

A. Fused vs. Single Sensor Approach

Results attained from the study illustrate that a multi-sensor approach to on-body location detection may not be necessary. A single sensor, the accelerometer, is capable of achieving results similar to the fused dataset, with significantly less drain on device resources, in terms of both CPU and power consumption.

Both pressure and light sensors attained results which were poor at best. Inclusion of the pressure sensor was considered of interest as this could potentially aid in differentiating between upper torso locations and lower body locations, using the altitude feature. However, with results of just 13% (balanced), the pressure sensor on the Galaxy Nexus proves inadequate for the task. Inclusion of the light sensor was considered to help differentiate between in pocket and out of pocket locations. While results attained demonstrate that the light sensor can certainly provide useful results on this front, some overlap exists between in the hand and breast pocket locations. When the smartphone was in the breast pocket of participants, it was typically upright, with the height of the smartphone larger than the height of the pocket, thus making the light sensor detect a significant amount of external light.

B. Walking as a Calibrator

This study required participants to walk around the track for each on-body location. Walking was selected as this provides a clean, easily distinguishable signature, visible to many sensors (e.g. accelerometer, magnetometer, gyro). For this to function correctly in real time, a lower tier activity classification routine would be required to successfully infer when walking occurs.

C. Proximity Sensor

Data obtained from the proximity sensor was not used to build models in this paper. Binary values returned from this sensor repeatedly fluctuated between close and far, when in a pocket or in a hand.

IX. CONCLUSION

In this paper, a feature set capable of distinguishing among several key on-body device locations was described. A feasibility study involving N=5 participants was carried out to test this feature set, using a variety of configurations over five different de-facto machine learners. Overall results are positive, with accuracies as high as 99%. This work demonstrated that it is feasible to differentiate from amongst a number of different on-body locations, using one or more smart device sensors. This study earmarks the accelerometer, as that which makes the highest contributions of any of the five sensors considered. Future work could investigate the role per-user sensor calibration can play when identifying the templates to use for location detection. This should be done with a larger number of participants.

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