Mobile Empathy: Putting the Mobile Device in its user's shoes

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ABSTRACT

Discovering the user's current physiological state allows a mobile device to self-adapt its behavior in such a manner that the services it provides to the user are delivered using the optimal modalities for the current circumstances. Furthermore, interpretations of the user's physiological state might allow its translation into an emotional state and emotional context awareness, which can opens the door to a new range of pervasive personal services. In this paper, we investigate the possibility of making a mobile device aware of where it is being worn on a users' body. We also propose an algorithm to allow the mobile device to understand its user's current level of activity without the requirement for strategically positioned sensors. This type of context awareness may enable us to design better interruption and alerting strategies, as well as informing the intelligent choice of interaction modalities on behalf of the device.

Categories and Subject Descriptors

H.5.2 **[User Interfaces]:** *Input Devices and Strategies, Interaction Styles*

General Terms

Algorithms, Experimentation, Human Factors

Keywords

Embedded Sensors, Gait Analysis, Context Awareness

1. INTRODUCTION

Knowledge of a user's physical activity state has been the subject of research for numerous fields of science. The analysis and quantification of human gait in particular, has allowed physicians to study and diagnose conditions such as cerebral palsy, Parkinson's disease and a range of neuromuscular disorders. Orthopedic treatment and post-traumatic care has significantly benefited from the study of kinematics, while recently gait analysis has been used to aid fall prevention and monitoring of physical wellbeing in older adults as in [1].

Gait analysis is carried out using dedicated and customized hardware and software systems. Photography and video are common low-tech approaches to gait analysis that depend on expert observation. More sophisticated systems, such as motion capture using active and passive "markers" positioned on a subject's body, are increasingly common and have become quite popular also in the cinema and film industry. Another approach to gait analysis uses micro-electromechanic sensors (MEMS), normally 1, 2 or 3-axis accelerometers, positioned strategically on a subject's body. These sensors measure the forces acting on the user's limbs and consequently translate these to motion.

A common example of gait analysis using MEMS is pedometers, or step counters. These are normally positioned (clipped) on a user's belt and measure the number of steps taken while worn, by monitoring vertical acceleration forces. Pedometer data has been shown to be useful for a range of purposes, e.g [2],[3],[4].

Accelerometers have recently started to appear as sensors embedded on common mobile devices, where they are used primarily as pedometers (e.g. Nokia 5500, SonyEricsson W710i), screen orientation sensors (e.g. Nokia N95), or alternative input modalities (e.g. SonyEricsson W910i – shake control). We believe that as accelerometers become more ubiquitous on mobile devices, they might become a useful tool for personal context awareness.

As previously mentioned, accelerometer data can be used to count users' steps. When observed over time, this count can provide a user's walking pace (slow, normal, fast, running). A person's walking pace can provide clues to their current emotional status. For example, one can think of a situation where a person is walking quickly to make an appointment, or rushing between desks and offices in a building to meet a particular deadline for a task. People in these situations are very likely stressed and preoccupied with their current activity and goal, thus being interrupted by their mobile device to receive a phonecall or an SMS would probably be frustrating.

2. Determining User Activity State

Pedometers are quite successful in measuring user steps, achieving an error rate of 5% for the most accurate type of devices. However, this is only possible if they are worn in an appropriate manner that affords them little freedom in relation to

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the user's limbs (upright position, clipped on a belt or strapped around the user's thigh). These conditions make measuring acting forces relatively simple: Acceleration on the vertical (Y) axis of the pedometer, which is aligned with the body's vertical axis, is all that is required to figure out whether a step has been taken. In contrast, users carry their mobile devices on or near their bodies, in various places and in a fairly loose manner that affords devices a fair amount of freedom of movement and rotation while being carried. This means that a device with a 3-axis accelerometer seldom has any of its axes properly aligned with the body's vertical axis when carried around.

The most common places for mobile devices to be carried are: trouser hip pockets, jacket and suit pockets (inner and outer), handbags, or neck straps. Walking and running affect variable force and acceleration patterns on these devices, depending on where they are worn. For example, head winds will flail an open jacket around, making the body only partly responsible for any movement of a device in a jacket pocket. Similarly, many female users carry their phones in handbags which move fairly independently of the rest of the body and tight-fitting trousers or jackets present rather inconvenient locations to store a mobile device. Finally, because mobile devices are randomly placed and carried, it is not reasonable to assume that monitoring a single axis can yield any useful results (Figure 1). This may be overcome if it were possible for the device to be calibrated every time it is worn on the user's body, so the position it is in before walking starts is computed. Naturally though, this would be rather inconvenient for any user, as they would have to stand still for some time after putting the device in their pockets or bag.

With a 3-axis accelerometer, which is commonly found on most sensor-enabled devices today, one can determine the overall forces acted upon the device, irrespective of its orientation, as a vector sum of the acceleration on the X, Y and Z axes. While not as optimal as determining the vector sum parallel to the user's Y axis (thus measuring only vertical forces), this requires no calibration of the device.

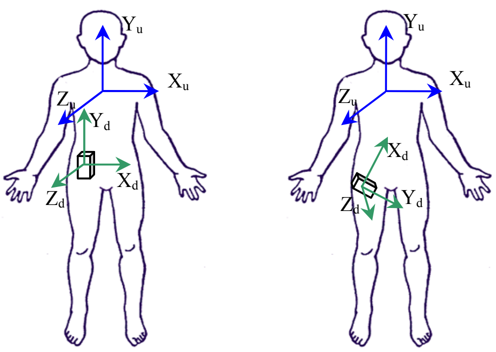

Figure 1: A pedometer's axes are well aligned with those of the body, when clipped on a user's belt (left). In contrast, a device's axes are randomly oriented in relation to the body axes when it is carried in a pocket (right).

3. GAIT ANALYSIS USING EMBEDDED 3-AXIS ACCELEROMETER

We began our analysis by observing the data patterns obtained when the device (SonyEricsson W910i) was worn on varying locations around a user's body. We asked 13 participants (8 male, 5 female) to walk the same fixed-length route at a comfortable (normal) pace with the device worn on 5 different locations, as follows:

Male Participants: Closed jacket inner pocket (CJIP), closed jacket outer pocket (CJOP), open jacket inner pocket (OJIP), open jacket outer pocket (OJCP), trousers hip pocket

Female Participants: Closed jacket inner pocket, closed jacket outer pocket, open jacket inner pocket, open jacket outer pocket, handbag

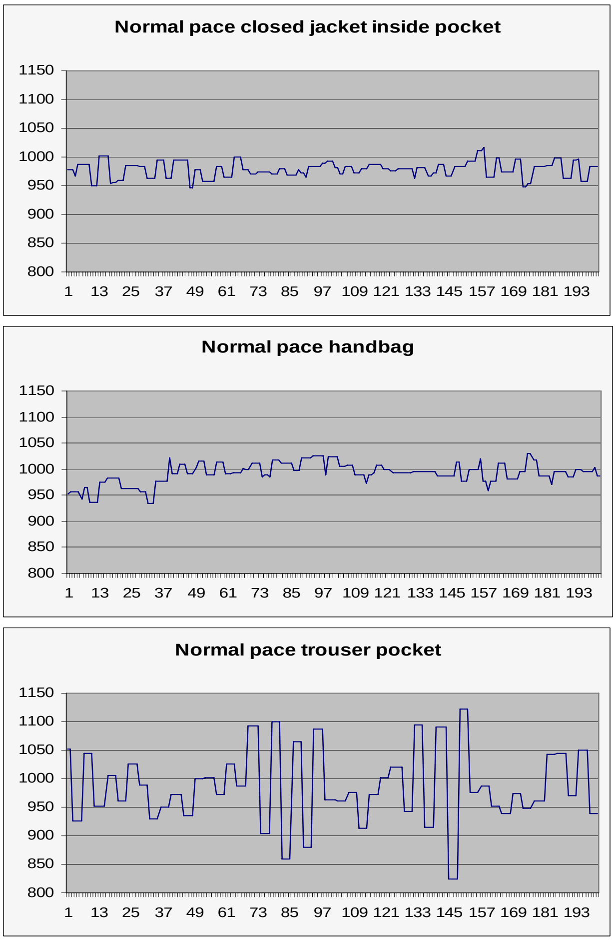

Figure 2: Examples of data output from various device positions (Y axis shows acceleration in milliG, X axis is the reading id)

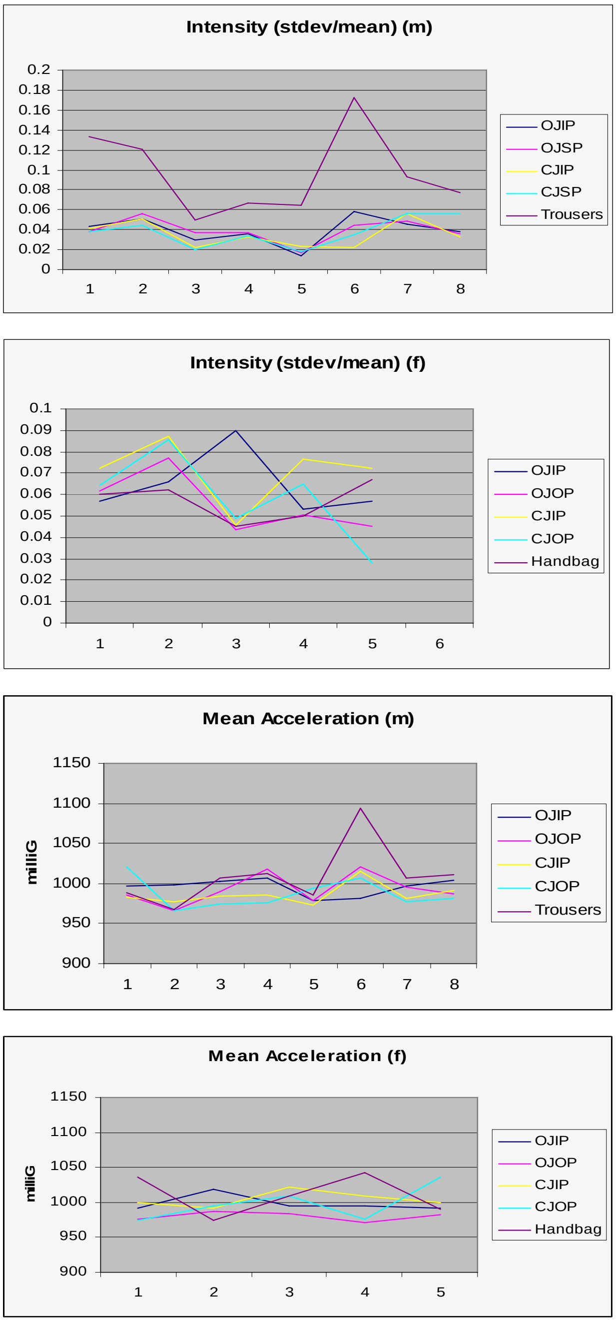

Figure 3: Acceleration intensities and means for various device locations on the body

Since every participant had different physical characteristics, the number of accelerometer data samples collected from each person varied (taller people required less steps to complete the route). For the analysis though, for each participant, we considered 200 samples from the median of the number of samples collected. We looked at the mean acceleration imparted on the device for each location, as well as the standard deviation, which we considered akin to "spectrum frequency" if the sinusoidal behavior of the signal data was taken into account. We also considered the ratio of standard deviation/mean as a metric akin to the "intensity" of the signal.

The graphical representations of our results (Figure 3) show that there is a distinctly higher signal "intensity" when the device is placed in the trouser pocket, which is somehow expected as many pedometer type devices perform optimally when attached to the hip. From these results we can also see that there is very little to distinguish the signal patterns when the device is located in other places in a garment. It could thus be argued that it is only possible to determine whether the device is carried in the trouser pocket or not.

4. PUTTING THE MOBILE DEVICE IN ITS USER'S SHOES

Looking at the actual data patterns of trouser pocket and jacket pocket and handbags (Figure 2), we observed that while a very clear pattern of steps can be detected in the former case, in the latter cases, it is very hard to determine whether steps have been taken as the "peaks" and "valleys" of the signal are relatively close in terms of absolute value. Table 1 below shows the relative inaccuracy of the embedded 3D accelerometer in detecting steps. To address this problem, we decided to pass the data through a transformation filter, based on the following logic:

$$\vec{T}_{(D_i)} = \begin{cases} \vec{D}_i \times (1-\tau), \vec{D}_i < \vec{D}_{i-1} \wedge \dfrac{\vec{D}_i}{\vec{D}_{i-1}} < 1+\lambda \\ \vec{D}_i \times (1+\tau), \vec{D}_i > \vec{D}_{i-1} \wedge \dfrac{\vec{D}_i}{\vec{D}_{i-1}} > 1+\lambda \end{cases}$$

$$D_i \ni [1000-a, 1000+a]$$

In this expression, $T_{(Di)}$ is the transformed data vector D_i, which is transformed through multiplication by $1\pm\tau$. The constant t is the mean "intensity" (stdev/mean) observed from measurements using the trouser hip pocket. The vector D_i is amplified by $(1+\tau)$ if its magnitude is greater than that of the previous vector in the measurement series and the ratio of the two is greater than $1+\lambda$, where λ is a threshold value that allows control of the "jitter" level in the signal. This is effectively the rate of change in the signal value to distinguish between jitter and actual force imparted on the device. Similarly if D_i's magnitude is less than that of its previous vector and the ratio of the two is less than $1-\lambda$, then the vector D_i is transformed through multiplication by $(1-\tau)$. A vector D_i is only transformed if it falls within one average standard deviation (a) of 1000mG (1000mG = acceleration on the device caused by the earth's gravity). The constant a is again calculated as the average of all standard deviations observed from measurements using the trouser hip pocket in our experiment.

5. Results & Conclusions

We performed an analysis of the effect of the vector transformation process on the ability of the mobile device to accurately measure the number of steps taken by the user. Again, we positioned the device in various locations around the body, and measured the average steps & detection rates for a fixed route for our participants. As can be seen in the graph below (Figure 4), the algorithm behaved correctly by amplifying the signal in situations where steps were actually taken, and was also successful in identifying the cases where the user remained relatively static.

Table 1: Percentage of steps not detected or over-detected using untransformed and transformed data (negative percentage shows overestimation).

Threshold=0.12					
	Raw	Trans-formed	actual	Raw Missed	Trans-formed Missed
Trousers	27	60	47	42.55%	-27.66%
CJIP	8	45	45	82.22%	0.00%
CJOP	10	55	46	78.26%	-19.57%
OJIP	8	54	47	82.98%	-14.89%
OJOP	9	54	47	80.85%	-14.89%
Average				**73.37%**	**-15.40%**
Threshold =0.13					
	Raw	Trans-formed	actual	Raw Missed	Trans-formed Missed
Trousers	23	50	47	51.06%	-6.38%
CJIP	7	29	45	84.44%	35.56%
CJOP	9	50	46	80.43%	-8.70%
OJIP	7	44	47	85.11%	6.38%
OJOP	8	44	47	82.98%	6.38%
Average				**76.81%**	**6.65%**
Threshold =0.14					
	Raw	Trans-formed	actual	Raw Missed	Trans-formed Missed
Trousers	19	46	47	59.57%	2.13%
CJIP	7	17	45	84.44%	62.22%
CJOP	7	42	46	84.78%	8.70%
OJIP	6	36	47	87.23%	23.40%
OJOP	7	34	47	85.11%	27.66%
Average				**80.23%**	**24.82%**

To measure the number of steps taken we observe the ratio between current and previous reading. If the ration exceeds a certain threshold, we consider the force as a step taken. The results obtained with the untransformed data and the transformed data are shown in Table 1.

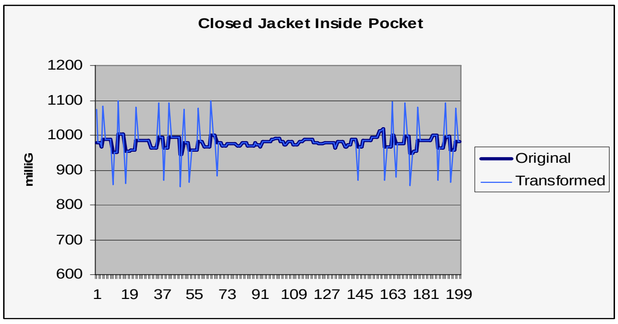

Figure 4: Transformed acceleration vectors. The middle part of the graph represents a period during which the user was standing, which was correctly interpreted by our algorithm

From this table, we can see that although our algorithm does not perform optimally in all circumstances, it can be applied to bring the accuracy of a pedometer function on a mobile device to usable levels.

Our conclusions and contributions from this work are two-fold: Firstly, we show that it is possible to distinguish between locations of the body where the device is worn but only between “trouser hip pocket” and “rest of body”. This can allow a device to choose the modalities it needs to use to notify its user (e.g. when in jacket, vibrate and ring at a medium volume, when in trouser pocket, ring loudly only etc). Secondly, we show that it is possible to amplify 3D accelerometer vectors using appropriate logic, in order to accurately estimate a user’s walking pace and subsequently make inferences regarding their emotional state. We are continuing our work in applying this knowledge in a range of situations, with the hope to investigate further the effect of our findings on decision support for user task interruption, location-based services and multimodal interaction with users’ mobile devices and services, such as self-adaptive music playlists, well-being applications and adaptive calendar reminders.

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