ADVANCED PEDOMETER FOR SMARTPHONE-BASED ACTIVITY TRACKING

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Abstract: This paper describes the design of an advanced smartphone pedometer developed as part of a larger solution aimed at encouraging a healthier lifestyle through regular physical activity, called Move2Play. Move2Play provides several motivational methods to promote exercise, some of which are based on the use of points derived from tracked activity. While current pedometers are easily tricked into counting steps by shaking the device, our advanced pedometer uses a neural network to detect and prevent this kind of cheating. In this paper, we discuss both the method for counting steps and our innovative approach to the recognition of cheating.

1 INTRODUCTION AND RELATED WORK

Evolution in IT has resulted in significant changes in our everyday life. Information has become ubiquitous, can be accessed almost anywhere and anytime and be leveraged to deal with our tasks more efficiently. Moreover, we now have access to new kinds of information previously unavailable. One such kind of information that can have a major impact is an overview of our everyday physical activity. Having this information is a basic prerequisite if we want to tackle one of the biggest problems of our society – the lack of physical activity, overweight and obesity.

This information can be captured and interpreted by an intelligent wearable device. However, the requirement to wear an additional measuring device is a key barrier to achieving long-term sustainability (Fujiki, 2008). It is therefore preferable to rely on a device people already carry, i.e. a smartphone.

Currently available solutions track users' movement "on-demand", mainly using GPS sensors. However, they are mainly used by already rather physically active people, while most of the people who need to become more physically active are unaware of such solutions or are not motivated to use them as they do not exercise regularly. We focus on such people who require additional motivation in order to become more physically active.

There is an activity we perform naturally, without paying much attention to it – *walking*. Walking reduces rates of chronic disease, ameliorates health care costs (Lee and Buchner, 2008) and is one of a few activities that every age group can and should participate in. However, over the last few decades, the amount of walking people do every day has been on the decrease, which has been one of the reasons of increased overweight and obesity and other health problems.

To change this, we track and analyse *walking* throughout the day, not "on-demand" but continuously, using smartphone sensors. Once captured, we provide users with a visual overview of their performance, which is the first step towards improvement. However, activity tracking and visualisation alone are insufficient, as the drop out rate is a serious problem even in professional training programmes and can be as high as 89 % (Iwane, 2000).

Therefore, we proposed a broader concept of comprehensive physical activity management, driven by various motivational factors supporting its users in achieving the required amount of daily activity. The process consists of recommendation of the appropriate amount of activity in the form of a personalised daily plan and automatic tracking and evaluation of performed activity. An important part of the process is the integration of different motivational factors, both intrinsic and extrinsic, which ensure its long-term sustainability. We implemented this process in a solution called *Move2Play* (Bielik, 2012). This paper describes the design of an important part of our solution – an advanced pedometer.

Most current smartphones come with an ac-

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celerometer, which is widely used by pedometer applications for step counting. According to (Marschollek et al., 2008), there exist only a few well-known freely available accelerometer-based step detection algorithms. Most of these approaches rely on threshold-based detection and they generally achieve sufficient precision.

Motivating people to be more physically active is a non-trivial task. In our case, we use measured activity as an input to motivational mechanisms such as various kinds of rewards. Especially with children, there is the risk that they will choose the easier path to get to the rewards offered, which means cheating, i.e., imitation of steps by shaking the phone in hand, becomes a problem. Current pedometers, both dedicated devices and phone applications, do not address this problem as they rely on motivated users.

2 STEP DETECTION BASED ON SMARTPHONE SENSORS

The accelerometer in a mobile phone sends events in regular intervals with the three components of acceleration (x, y, z), which range between -1 and 1. Because the orientation of the phone inside the pocket is not known in advance and may be different each time, it is convenient to track the changes in the direction of the vector of acceleration. For this purpose we use the dot product of two consecutive accelerations. Given normalised vectors, this is the cosine of the angle between them – let it be d (1). When the phone stops abruptly and reverses direction, this angle should equal 180°. In practice, this is rarely the case, since the phone slips inside the pocket.

$$d_i = (\cos\alpha)_i = \frac{x_i x_{i-1} + y_i y_{i-1} + z_i z_{i-1}}{\sqrt{x_i^2 + y_i^2 + z_i^2}\sqrt{x_{i-1}^2 + y_{i-1}^2 + z_{i-1}^2}} \quad (1)$$

During inactivity and between successive steps, d equals 1. A negative peak (a decrease below a threshold) is considered a step. This threshold is different for the left and right leg, depending on which is closer to the phone. To increase the precision of the measurement and to filter out noise, we use a weighted moving average of the last 10 values of d (2).

$$WMA_{10}(d)_i = \frac{10d_i + 9d_{i-1} + \cdots + d_{i-9}}{55} \quad (2)$$

Figure 1 shows 20 walking and running steps. In case of walking, it is straightforward to recognise steps taken with the right foot from steps taken with the left foot. In case of running, the difference is not sufficiently recognisable.

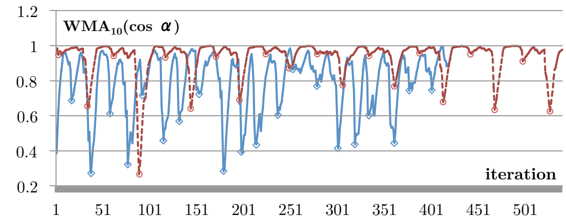

Figure 1: Walking (dashed line) and running (solid line) – 20 steps (LG with Windows Phone 7).

Figure 2 shows two forms of cheating, slow and fast shaking of the phone in hand, in contrast to walking. Similarly to previous figures, the lines denote the weighted moving averages of d values as given by (2). Greater regularity can be seen in both forms of cheating than in walking or running, as well as more frequent alternation of minima and maxima. The weighted moving average often does not reach the value of 1, as is the case in between walking and running steps.

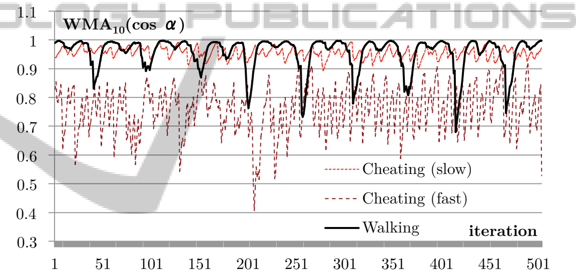

Figure 2: Cheating by slow and fast shaking of the phone in contrast to walking (iPhone).

Our algorithm utilises threshold-based detection of steps with different thresholds for left and right legs. When the weighed moving average as given by (2) decreases below these thresholds, the algorithm increments the step count. The thresholds are defined differently for various models of smartphones and are based on experimental results. The values for the particular devices are shown in table 1. In the next stages of development, the Wolf method may be used to eliminate the hardware-specific constants.

The algorithm takes several attributes of walking into account:

- the alternation of the left and right legs – via specific thresholds,
- vibrations after the foot strikes the ground – using:
  - minimum step duration,
  - minimum required deceleration computed for a given value of d before acceleration can take place.

The core logic of our algorithm without the above considerations every hundredth of a second executes the following steps:

1. Calculate the current value of d using (1) and average using (2).
2. If the average is lower than the threshold for the right (left) leg: increase the step count.

Table 1: Thresholds for step detection.

	iPhone	HTC HD7	Samsung Omnia 7 LG Optimus 7
Right leg	0.96	0.97	0.9
Left leg	0.98	0.995	0.985

3 INTELLIGENT DETECTION OF CHEATING

Figure 2 shows the striking difference between walking and cheating, which can be described as a difference of patterns. Searching for patterns in measured data can be done in several different ways. One solution is the creation of a decision tree. However, unlike a decision tree designed to simply count steps, a tree capable of detecting those patterns of cheating that make it different from walking or running, would necessarily be considerably more complicated.

A common solution to problems which involve a search for patterns in measured data is the training and application of an artificial neural network. This is the approach we explore and test the applicability of.

Given that the solution is to be deployed on a mobile platform, where computational complexity is undesirable because of battery life constraints, we chose a feedforward neural network with one hidden layer. We opted for 50 input neurons, which is the number of weighted averages of d calculated each second. It is also the approximate number of averages necessary to distinguish between cheating and valid activity using the unaided eye, the patterns being clearly visible. We need only a single output neuron, whose output value we defined as 0 for valid activity and 1 for cheating. We prepared a total of 269 training sets of 50 inputs. Following an analysis of the input sets, we chose the incremental training method as the most suitable one. We found that the sigmoid function is the most suitable for the hidden layer, whereas the linear symmetric function was chosen for the output layer.

We implemented the neural network in our application for the iOS platform, i.e., for the iPhone. We used the FANN Library[1], one of the best-known and most widely deployed libraries for training and the application of artificial neural networks.

In order to evaluate the neural network, we created separate sets of measured data for walking, running and cheating. Figure 3 shows typical outputs of the neural network for walking. When determining whether or not the user is currently cheating, a weighted moving average of the last 4 outputs of the neural network is used. As can be seen, the average rarely exceeds the value of 0.5.

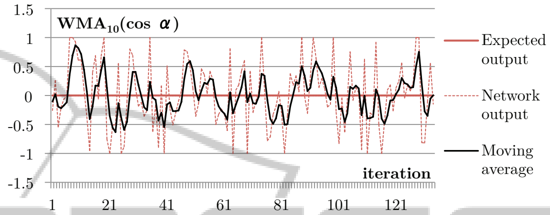

Figure 3: Outputs of the neural network while walking.

Figure 4 shows typical outputs for running. As can be seen, the neural network has a higher tendency to classify running as cheating compared to walking. In spite of that, the weighted moving average of the last four outputs rarely exceeds the value of 0.7.

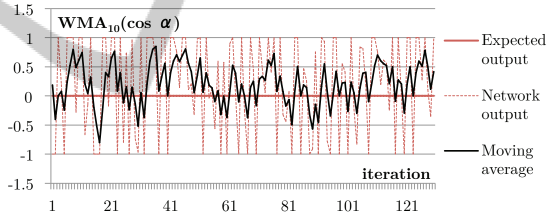

Figure 4: Outputs of the neural network while running.

Figure 5 shows typical outputs of the neural network for cheating, which significantly differ from the previous values for walking and running.

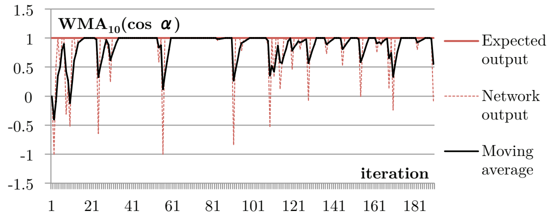

Figure 5: Outputs of the neural network while cheating.

The most frequent output of the neural network when cheating is 1. The weighted moving average of the last four outputs mostly stays above 0.5.

Table 2 shows a comparison of the desired and average output of the neural network. The results are

[1]The Fast Artificial Neural Network Library is available at: http://leenissen.dk/fann/wp/

sufficiently accurate for walking. There is room for improvement especially in the case of running.

Table 2: A comparison of the desired and average outputs of the neural network.

Activity	Sample size	Desired output	Average output	Standard deviation
Walking	693	0	0.0612	0.3175
Running	151	0	0.2116	0.3654
Cheating	251	1	0.818	0.257

Solving the Problem with Punning. At first glance it may seem problematic to distinguish running from cheating, since the outputs of the neural network frequently overlap. The solution involves the current minimum of d from (1), which will be lower for running steps than for walking steps. This is also the case with fast as opposed to slow shaking of the phone in hand during cheating.

The problem can be solved using a moving threshold between valid activity and cheating. As an example, a threshold of 0.5 can be chosen for values typically measured when walking or cheating by slower shaking. As more vigorous activity is detected, the threshold may be raised to a higher value, such as 0.7.

This is possible as a consequence of the fact that more intensive shaking sees the neural network produce outputs of 1 with a higher probability than slower, less intensive shaking. The moving threshold can therefore be used without fear of misinterpretation of cheating for running.

It is important to realise, though, that in the current state the neural network fulfils the purpose it was designed for. The purpose of the implementation of the neural network was not to detect cheating with an accuracy of a hundred per cent. First and foremost, the purpose was to discourage cheating by making it sufficiently difficult and tedious, so that it is more rewarding to take a walk and receive points for real activity. The current implementation of our neural network meets this goal.

4 CONCLUSIONS

In this paper, we describe the design and implementation of an advanced smartphone accelerometer-based pedometer, which uses an innovative approach to the detection of cheating. This is important for applications where activity is a base for rewarding and there is no natural way of ensuring motivation for being active (typically for children).

We have based our solution on the recognition of patterns characteristic to cheating. To that end, we have successfully trained and used a feedforward artificial neural network. The results we have obtained in evaluation confirm the applicability of an artificial neural network for the detection of cheating. We have been able to detect cheating with a sufficient precision and have thus met our goal of discouraging potential users from such an activity.

We have developed our advanced pedometer as part of a larger solution. Specifically, the pedometer is part of the activity tracking module of our *Move2Play* system. The activity tracking module uses GSM signal strength fluctuation analysis to determine whether an activity is taking place or not and thus to save battery life (Bielik, 2011). Activity tracking together with personalised activity recommendation and evaluation are the essential parts of our solution. In order to evaluate our solution, we realised its specialisation called *Move2PlayKids*, which depends on the intelligent pedometer module as children who need to exercise more tend to cheat.

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