MENTAL HEALTH DECLINE PREDICTION
A Smart Sensor for Day to Day Activity Recognition

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Keywords: Mental health, Depression, Activity sensing, Wearable Smart sensor.

Abstract: The ambulatory activity of a person may be used as one component within an overall wearable sensor system that predicts the onset of mental health problems. Ergonomic smart sensors that can determine the total energy expenditure and type of ambulation may provide unique insights to the coping behaviour of stressed people. Rather than relying on wearable computers, a single smart miniature sensor that is worn 24/7 should perform the complex embedded recognition tasks while meeting difficult battery life, wireless communications and ergonomic constraints. The development and testing of such a smart sensor is described which takes into account action timeline variations, as well as action variations both intra individual and inter individual.

1 INTRODUCTION

This work relates to an activity recognition sensor developed within the EU research project OPTIMI. The project's aim is to provide on-line predictive tools for the early identification and intervention during the onset of a mental illness, in particular depression, following the inadequate coping with day to day stress.

Second only to depressed mood itself, tiredness, low energy and listlessness are the most common symptoms associated with depression (S. M. Stahl, 2002). Energy loss in depression is the factor that correlates most strongly with lost productivity and lack of social functioning.

The Psychological Counselling Centre, which acts as the primary support for students at the ETH Zurich and University of Zurich, recognize that students who are significantly traumatized by examination stress and border on mild depression will disengage from social activities, sports and any events requiring physical involvement. Group activities are avoided, and the student will prefer to stay at home and do nothing.

The exact relationship between activity and depression is not clear. In a study on 956 Japanese men diagnosed with metabolic syndrome (T. Takeuchi, 2009) it was shown that the deposition of fat around the waist line, was a predictor for the onset of depression. By studying the behaviour of the control group the conclusion was that a healthy lifestyle that involves regular exercise alleviates depression while conversely a sedentary lifestyle may increase the visceral fat of individuals with metabolic syndrome, thereby increasing the risk of depression. In other related work (A. Berlin, 2006) it was shown that an enforced reduction in daily exercise resulted in symptoms of depression.

It is very difficult to find conclusive research that depression causes a loss of energy and activity. However what seems to be widely agreed is that activity and sport has a positive effect in reducing depression and a reduction in exercise is associated with the onset and ongoing depression. The quantity and type of exercise that one performs per week that might predict the onset of depression has not been studied to our knowledge and should be determined as one outcome in the OPTIMI project.

In the field of physical activity research, see the Compendium of Physical Activity (B. Ainsworth, 2000), there exists an alternative to measuring energy in Calories or Joules. For example one MET

Kaegi-Trachsel T., Gutknecht J. and Majoe D..
MENTAL HEALTH DECLINE PREDICTION - A Smart Sensor for Day to Day Activity Recognition.
DOI: 10.5220/0003150002190227
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2011), pages 219-227
ISBN: 978-989-8425-34-8

(for 1 unit of metabolic rate) corresponds to the typical energy consumption when at rest. Running at 17Km/h has been found on average to correspond to around 10.0 METs.

Having studied the Compendium, the activities that are most likely to reduce as the onset of depression occurs are mainly ambulatory activities such as Bicycling, Sports, Dancing, Walking, Running, Stairs and Hill climbing. The table below shows some of the MET values for each activity.

Table 1: METs for different activities.

Code	METs	Activity Description
01015	8.0	Bicycling
03031	4.5	Dance: Disco, Folk, Country
15711	8.0	Sport: e.g. Volleyball, Gym
17151	2.0	Walking, less than 2.0 mph,
17231	8.0	Walking, 5.0 mph
15734	10.0	Running, sprint, athletics

Rather than compute actual energy expenditure in calories, it is convenient to try and count the MET minutes product used by a person per day. Once one can identify what ambulatory activity is being performed then the total time spent during each activity provides a simple way to measure and compare people's daily behavior.

In other related research it has been shown that there is a relationship between a person's gait or walking style, and their depressive symptoms (J. Michalak, 2009). However the primary impact of depression is on the upper body posture and the speed of walking, not on the leg posture or the action cycle of the legs. Therefore we do not expect depression to affect ambulation patterns.

In summary, as part of a multiple sensor solution, an activity sensor that can recognize the different ambulatory activities is being developed and this paper reports on the success to date.

Section 2 describes the OPTIMI architecture within which the activity sensor operates. Section 3 describes the sensor hardware while section 4 explains the recognition approach and section 5 discusses the results obtained during preliminary trials.

2 SENSOR ARCHITECTURE

The OPTIMI project incorporates a number of smart wearable sensors. The following summarizes the sensors and their target function:

- The Activity Sensor (ACT) for ambulatory activity recognition, described in this paper
- ECG for heart rate derived stress indicators
- EEG to derive affective status (sensitivity)
- Sleep Quality, restlessness and insomnia
- Sub Dermal Cortisol
- Speech Analysis to estimate depression

In many wearable sensor applications, data from the sensor is streamed to a signal processing computer such as a wearable PDA. This approach can result in a 90% wastage of the available sensor battery energy in wireless communications and sensors that are worn 24/7 would require frequent recharging.

Instead significant energy conservation can be achieved by making the sensor itself do the signal processing using highly optimized signal processing in which the large amounts of real time information are processed and converted to time stamped results comprising only a few hundred bytes per day. When this data is communicated wirelessly not only is their little energy spent on communications but in addition raw data privacy and data security are enhanced.

Therefore the policy in OPTIMI has been to process data at source as far as possible and to derive a much smaller encrypted set of time stamped data reflecting the state of the user. As a result the activity and ECG sensors process data locally all day long and store the results locally. At one time during the day, the user is invited to update their daily diary hosted on a Home PC as well as use the speech and EEG sensors. While these tasks are being carried out the ECG and ACT data is wirelessly downloaded.

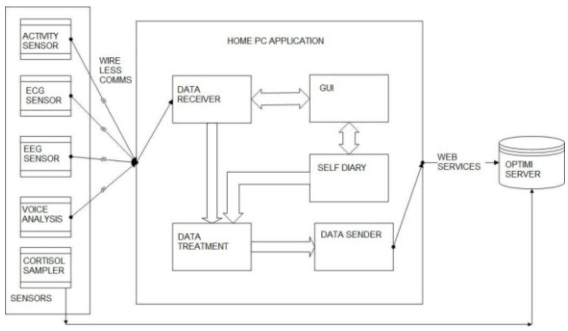

Figure 1: The OPTIMI sensor and Home PC Architecture.

3 SENSOR HARDWARE

The ACT hardware is based on the nRF24LE1 from Nordic. This micro-controller was chosen despite its limited processing capability, based on its very low cost, very small footprint, suitable ADC and flash

EEPROM resources and the integration of a 2.4Ghz RF transceiver.

The nRF24LE1 is combined with an Analog Devices ADXL325 three axis accelerometer for the purpose of measuring accelerations of the user's lower leg; the sensor being placed just above the ankle.

The microcontroller samples the three axes at a rate of 50 or 100Hz and performs activity recognition processing on this data. Following each sample and activity identification the sensor logs the result in the EEPROM, time stamps it and continues to the next activity recognition.

Due to the fact that the RF end of the microcontroller consumes a large proportion of the power, the RF stage is seldom switched on during normal operation. However every 5 seconds, the RF stage is switched on for 20 milliseconds and the device listens for a command packet from the users Home PC. In the event one is received the sensor begins an authentication handshake and subsequent interchange of relevant data.

As the device is to be worn continuously three very important design constraints have been demanded:

- The battery life must be as long as possible
- The device must be small and hermetically sealed to survive swimming and bathing
- The device must therefore be non contact charged

The device is powered by a 20mAh lithium polymer battery with the intention being to last ideally 72 hours between charge times. Besides reducing any unnecessary usage of the RF stage, as previously mentioned, the design includes several energy saving methods.

For example the ADXL325 device has been chosen for its wider G range and very low cost however it is slightly more power hungry than other devices available and is the main power-sink after the microcontroller. To reduce power applied in sensing the accelerometer and the microcontroller ADC are only switched on before and switched off immediately after the 3 axes are sampled. Allowing for switch on times delay, this saves about 50% of the power compared to leaving them on at all times i.e. saving roughly 0.15mA on average.

Similarly, it is planned that the activity recognition task should itself be managed depending on time and observed activity. That is, by using the local timer and sleep function, the sensor will set to conduct activity recognition between around 10% and up to 70% of the time, depending on the observed activity seen by the accelerometer.

This is achieved by implementing a small dedicated code to check the accelerometer outputs and to decide if there is some activity or not. If there is no activity, then the device goes to sleep for 100 milliseconds before repeating the activity check. As soon as activity is detected the main recognition task is engaged and repeated up to a maximum of 70% of the time, the rest of the time the sensor is set to sleep mode.

In this way if the user is continuously active, such as engaged in a long walk, the energy maximum usage is 70% of worst case. Meanwhile if the user is sleeping, then the sensor is largely inactive apart from if the user moves from time to time.

3.1 Ergonomics Constraints

The small size of the sensor, Figure 2.0, has been achieved using an electronic PCB design equal in size to the dimensions of the LiPo battery used. The assembled device has a very low profile with no on-off switch or flash connectors.

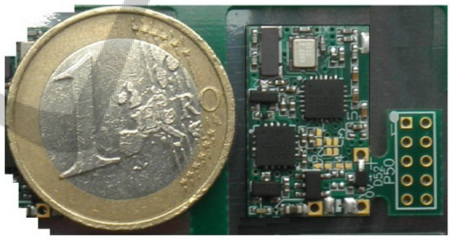

Figure 2: The ACT sensor, 20mm x 12 mm x 3mm, the flash connector on the right is snapped off pre encapsulation.

The hermetic sealing requirement implies that the sensor must have a contactless charging method and that the sensor is totally encapsulated.

To achieve this, the ACT sensor incorporates a LiPo battery charging circuit as well as the rectification stage for an inductive voltage power input. The microcontroller, powered by the battery, is able to sense when the rectified inductive input voltage rises above the input threshold required by the charging circuit. When this occurs the microcontroller goes into a deep sleep effectively switching itself off and appearing as a tiny load shunt across the battery. This allows the charging circuit to charge the LiPo battery without any interference, until the battery voltage has reached the fully charged level.

Meanwhile the inductive loop coil which is driven at 10KHz by a standard off the shelf inductive power supply, is integrated into the strapping system used to attach the sensor to the users lower leg.

Figure 3.0 shows a device under inductive charge. The electronics is sealed within a two part epoxy resin (ALH Systems Ltd., U.K.) that has been chosen to provide maximum water resistance, maintain hardness to over 80 degrees C., and above all to be extremely toxic and irritant free when worn against the skin. Further the color and molding of the resin is chosen to create a device that could be worn as a fashionable accessory.

Figure 3: The ACT sensor in encapsulation and on inductive charge.

4 RECOGNITION APPROACH

Activity recognition for health purposes has become a much researched topic. The measurement of activity has major implications for diseases such as obesity and is important for monitoring and assisting the elderly and disabled. Several research works have attempted to detect user activity using motion sensing [6, 7, 8].

Having reviewed the state of the art, two major design issues were considered important in this work. Firstly, how to cope with variations in the time taken to complete an activity and secondly whether a sensor should be trained for its own user or if a generic user independent method could be created.

The recognition approach itself requires a feature extraction followed by a machine learning of the classification parameters and essentially two methods exist namely discriminative and generative. In many of the discriminative approaches, time is an important dimension. For example most high end pedometers and more ambitious work (U. Maurer, 2006) use time domain statistics exclusively to extract the features. Similarly frequency domain power spectral density may also be used, (M. Lee, 2009). In these cases how fast or slow the action is performed factors into the type of activity classification. This can result in different interpretations of whether a walk activity is a fast walk a slow walk or a slow run.

In the generative approach, the feature extraction must generate a sequence of observations and these could be treated as time invariant; just a list of codes. If one can achieve total time independence then how fast or how slow the person performs the activity does not factor into the recognition problem.

In order to provide a generic classifier that can recognize anyone's activity based on a general training, it was felt that a probabilistic approach should be used that would include a wide range of user variations.

Combining these two considerations, what was decided was that a probabilistic generative approach that excluded time during the feature extraction process was necessary. Both feature extraction and learning classifier should combine to detect the activity at a general level rather than to detect the specific users activity cycle. In this way the user simply applies the sensor to their leg on a plug and play basis and does not need to engage into a specific one to one training procedure.

In a similar approach to (J. Suutala, 2007) we have used a simpler k-means approach, rather than SVM approach, to derive a time independent observation feature space followed by a Hidden Markov Model approach for the observation sequence processing and classification.

4.1 Feature Extraction

As discussed above, the time dimension is preferably excluded from our analysis. By doing so we attempt to detect walking, irrespective of whether the walk cycle is a slow walk, a medium walk or a brisk walk cycle.

When one studies the ambulatory cycles of walking, running, climbing and so on it becomes clear that while there are several similarities, there are also differences. Specifically the sequence of rotations and jerks of the leg are different

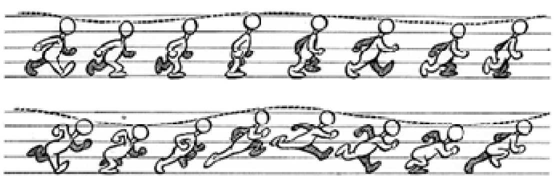

Figure 4: The walk cycle versus the run cycle showing leg rotation difference particularly during the flight phase.

irrespective, to a large degree of the time over which they occur.

The legs rotational posture can be sensed by the 3 axis accelerometer which detects leg inclination relative to the gravitational field. The leg jerk accelerations are then superimposed on the gravity signal.

Except for the case of dance and sports, where the leg often moves in the Z direction, from left to right, for walking and other ambulation, the main accelerations occur in the sagittal XY plane.

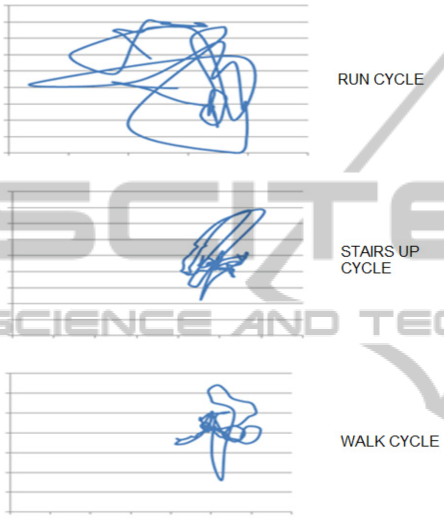

Figure 5: X vs Y plots of the accelerometer axes for running, stairs and walking.

In Figure 5.0 above the X and Y axis readings are shown for walk, run and climbing stairs. The readings are shown as a line plot of X against Y. One can see that the readings map out three totally different looking plots and these plots tend to be largely time invariant, looking roughly the same irrespective of the time taken to do the motion. Therefore these X vs Y plots are the base for the time invariant approach where the objective is to define key points in the plot that can be used as features.

If one looks at the related time plots for this data, see Figure 6.0 below, one can see that in the time domain, it is possible to quickly identify by eye the specific parts of the action cycle corresponding to a feature of the activity. An example in the run cycle is the point of “flight” where we can predict both of the user’s legs are off the ground, or in the stair climb, where the leg is lifted to the next stair as opposed to pushed forward in the case of the walk cycle.

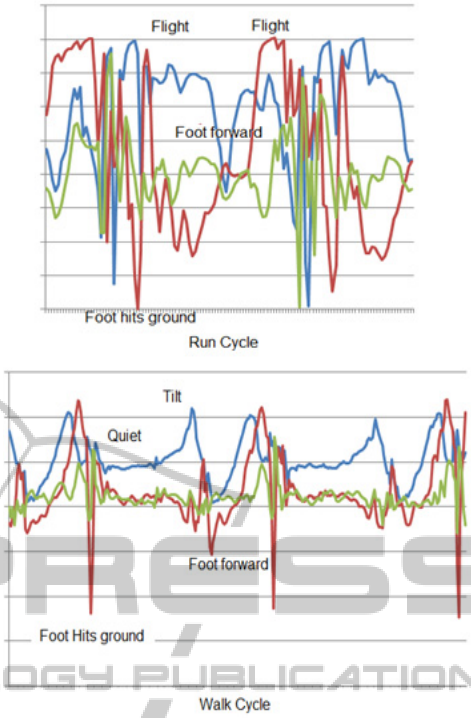

Figure 6: Annotation of the run and walk cycle indicating primary sequence points.

Instead of using time references to mark these points of interest we alternatively use X, Y coordinates in the 2D XY space. These reference points allow us to quantize the raw data and assign it a code thereby defining an observation. Each observation code becomes an input to the final HMM classifier that will recognize the activity.

To automatically create the points for a specific activity we apply a k-means algorithm to the XY data generated during that activity cycle. This results in a much smaller number of points that represent the overall plot by a set of region points or zones of interest. Such a technique was successfully used in previous work conducted by the authors in a Tai Chi activity recognition where points were mapped in a 3D space, (D. Majoe, 2009).

These zones are calculated as the centroids of the standard k-means algorithm, which was modified to accentuate the weighting associated with each data point. Since the most interesting data points in the activity cycle are those where the leg is moving, so the weighting of a data point was calculated as a function of the square of its velocity. In addition, to de-accentuate the high number of XY values that occur when the leg is stationary and vertical, a “quiet” point, the weighting is increased as a function of the square of the distance away from the "quiet" point.

As a final measure, one or two of the centroids calculated can be slightly moved by hand to further accentuate a specific zone of interest. The centroid distribution for an example walk cycle is shown in Figure 7.0 .

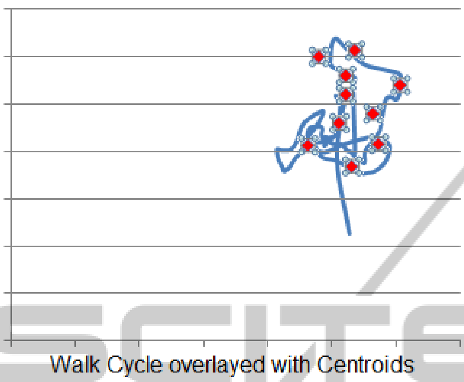

Figure 7: K-means Centroids for the walk cycle.

Having calculated the M centroids, in XY space, the sequence of observations for the HMM is calculated as that sequence of centroids closest to the flight path of the activity signal as it moves over the XY space. In this work the number of centroids M was finally set at 15, giving 15 possible observation values.

4.2 HMM Recognition

The HMM recognition method has been well described and documented (L. R. Rabiner, 1989). The method allows the modeling of a state change process which associates to each state an emission probability for a given sequence observation occurring. Therefore the XY space derived activity observations, coming from the feature extraction, may be associated with a probability of occurring at a specific stage of the state change process. If an observation does or does not occur at a point in the sequence finally corresponds to a higher or lower probability being estimated.

Since one has no clear idea of what the hidden state model should be in the case of the various ambulation activities, one relies on the Baum Welch learning algorithm to define the state model and no restriction is placed on the state transition matrix.

Through our experience with work on activity recognition, the optimal number of states used is 5 and the observation set is kept to 15. For each activity to be recognized we use a sliding window of variable length, between 10 and 20 sequence observation changes.

In order to train the classifiers for a particular activity, for example for walking, the following process is performed:

- Collect 9 walk cycles for volunteer 1
- Generate k-means zones for all data
- Adjust key centroids by hand
- Generate Observation Sequences
- Input Sequences to Baum Welch algorithm
- Save Output matrices

The output matrices reflect all that is needed for running a classifier for this activity. To make a classification, the forward probability algorithm is applied using these matrices on the test observation sequence data. The forward algorithm generates a number closer to 1.0 the better the correspondence of the test sequence to the training set. In order to create a suite of activity classifiers the above is repeated for all activities and a bag of classifiers is used with maximum probability voting logic to determine which activity has been performed.

To judge inter individual recognition, data from multiple volunteers is merged to create a general activity feature extraction centroid reference base. Since there are differences in the way people walk and run it was hypothesized that the recognition rates would be significantly lower than for the individual trained approach.

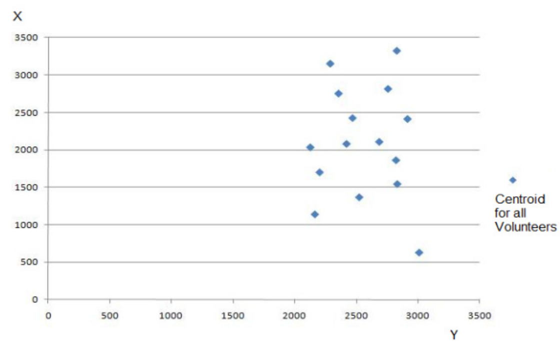

Figure 8: Generalized Centroids formed from all the walk cycles of all Volunteers.

Recognition rates will be acceptable provided the inter individual and intra-individual activity patterns are similar and that the feature extraction and HMM classifiers can make use of these similarities. The centroid pattern generated by the k-means algorithm should be similar whether it is for one person or for multiple people's activity cycle data. That is, zones of interest will have a similar visual pattern for both inter and intra individual activity cycles.

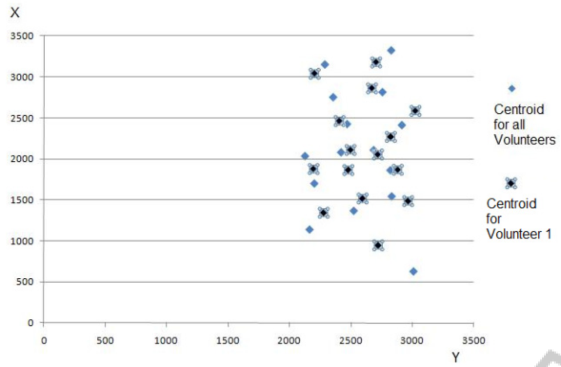

Figure 9: Overlay of Volunteer 1 on the Generalized Centroids of all 12 Volunteers.

The above plots clearly show that the feature space generated by using data from all volunteers, Figure 8.0, closely resembles, when overlaid with data from a single volunteer, Figure 9.0. The two sets of centroids demark a similar visual pattern and this allows us to conclude that the walk cycle activity is generally speaking the same for all volunteers. The same was found to be true for other ambulatory activities.

5 RESULTS

In order to obtain test data a trial, which received full ethical approval from the Ethics Commission of ETH Zurich, was conducted in Zurich. Twelve volunteers were fitted with the sensors and a wide range of activities were recorded:- Walking, Running, Jogging, Cycling, Stairs Up, Stairs Down, Walking up Hill, Walking Downhill, at rest and playing catch ball.

The primary aim of this trial was to check the sensor hardware and verify the base algorithms. So far we have determined initial recognition accuracies for walking, running and stairs up for inter and intra individual recognition.

5.1 Sensor Hardware

The sensors were used in two ways. At first they were used simply as data recorders, sampling the activity cycles as the volunteers walked around the Zurich city centre and then downloading the data wirelessly to a Net-Book afterwards. In order to perform most of the algorithm development, the recognition analysis was then done offline on desktop PCs.

Following the training of the classifiers and once the emission, state and transition matrices had been obtained for each specific activity, the HMM Classifier based on the forward algorithm was run on the ACT sensor embedded as an application. This was done to assess the computational load in a real time situation.

The feature extraction and recognition on the ACT device is performed as follows:

- Sample Motion Data for 5 seconds at 100 Hz.
- Generate Sequences for each activity
- Isolate the first occurring “quiet time” observation
- Apply forward Algorithm from this point
- Majority vote for highest output classifier
- Store results and loop back to sampling

The HMM computation performed on the sensor is restricted to the forward algorithm for each of the activity classifiers of interest. Acting as a dedicated activity recognition device, the ACT is very easily reprogrammed with a new activity recognition task by simply uploading different HMM matrices as data files over the wireless interface.

The low power nRF24LE1 running at 16Mhz has two main challenges, to perform the feature extraction front end and generate the sequences as quickly as possible and then to calculate the forward probability as fast as possible for each activity.

The processing times measured on the sensor, for different conditions are as follows:

FEATURE EXTRACTION	
Configuration:	15 centroids
Number of samples:	100
Execution time:	459 ms
Number of samples:	50
Execution time:	230 ms

HMM CLASSIFICATION	
Configuration:	5 HMM states
Observation types:	15
Sequence length:	20
Execution time:	29 ms
Sequence length:	10
Execution time:	13 ms

These results help us to decide how to structure the overall quasi real time recognition algorithm. Given these values, it should be possible to sample data for 2 seconds at 50 Hz (encompassing all types of cycle) and follow this with 0.5 seconds of processing for the feature extraction followed by 10 classification activity types (walk, run, cycle etc.) taking up another 300ms. So at maximum we sample for 2 seconds and process off line for 1 second and this confirms that the use of the nRF24LE1 is acceptably powerful for this recognition processing task.

Figure 10: Trial volunteer walking on a road and sensor located against right lower leg.

5.2 Early Recognition Results

So far the feature extraction and HMM classification have been tested with data from the 12 volunteers. This is probably insufficient data for a robust and full training of the classifications, however what was required was a proof of concept feedback at this early stage of the work. In particular we wanted to know if one can apply a generalized recognition approach where individuals do not need to train their own sensors.

Table 2: Confusion Matrix showing the percentage of detections for a given activity (row) for each classifier (column).

	Bike	Run	Stairs	Walk
Bike	45	0	44	10
Run	0	90	10	0
Stairs	1	6	90	3
Walk	0	0	22	78

The activity data from all volunteers was split into one third training set and two third testing set. The trained classifiers were run with the data from all test cycles. Voting between classifiers was then performed to select the highest probability output classifier.

The above results are very encouraging as a notional target of 80% was initially considered an acceptable accuracy in assigning MET energy values to different activities. On investigation the poor result, 45%, for the Bicycle activity was caused by vibration noise that had not been filtered out. The misclassification of the Stairs classifier has been tentatively explained by the limited training data though more work is needed to fully explain it.

6 FURTHER WORK

The approach has been evaluated on 12 volunteers. It is planned to increase the size of the trials to 50 volunteers and to obtain the activity data for different people (size, age, shoes and clothing), in different settings and over longer periods. Given this data the algorithms will be further improved and tuned.

In order to improve the sensor's ergonomics, user acceptance and usage compliance, a usability study has been started in which various alternative shapes and strapping methods should lead to higher 24/7 wearability.

In order to map the relationship between depression and activity, calibration trials with 300 users in three countries are planned to begin in 2011. Coping strategy trials will begin in 2012.

7 CONCLUSIONS

A smart sensor that performs the task of activity recognition on a daily basis has been presented. The hardware design achieves several of the goals of accuracy, wireless data transmission, miniaturization, low cost, hermetic packaging with inductive charging and long battery life through attention to power management.

The level of activity recognition achieved thus far is promising. In particular it has been shown that the sensor at this stage can already offer a high level of activity recognition accuracy. Most importantly it has been shown that ambulatory activities can be generalized and that individual sensor training will not be necessary.

ACKNOWLEDGEMENTS

Acknowledgements go to the support students at ETH Zurich and the co-funding received under the EU IST Framework 7 program for the project OPTIMI www.optimiproject.eu.

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