Very Low Complexity Algorithm for Ambulatory Activity Classification

J. Solà i Carós*, O. Chételat*, P. Celka** and S. Dasen*

* Swiss Center for Electronics and Microtechnology (CSEM), Neuchâtel, Switzerland
** School of Engineering, Griffith University, Queensland, Australia

jsa@csem.ch

Abstract: The present work introduces a novel set of features for the classification of the following human activities: standing/sitting, lying, running, walking flat, walking upstairs and downstairs. A binary classification tree is then used for ambulatory activity classification tasks which require low complexity processing. The set of features is extracted from a single vertical axis accelerometer placed on the thorax of the subject and is based on a single stride detection algorithm. When a rhythmic activity is detected, the system performs the activity classification at a single stride cadence in a three dimensional feature space: together with a stride energy estimation, a novel feature achieves the detection of stairs events. Finally, when no rhythmical movement is detected, the system successfully discriminates between standing/sitting and lying, by estimating the projection of the gravitational vector.

Introduction

At all ages, humans are performing motion for accomplishing daily activities. Important information on human health is contained in the human motion during day and night, such as the daily relative percentages of walking or running with respect to resting. These relative percentages can be used as markers for potential psychological disorders, such as stress or depression; and physiological pathologies such as heart disfunctioning, hypertension, diabetes and obesity [1, 2]. Therefore, such indices are of particular interest for psychotherapy, preventive medicine and rehabilitation management in-hospital and out-hospital. In addition to relative daily percentage of activities, motion captured by accelerometers can reveal relevant information on the gait. In particular, acceleration signals recorded by three dimensional orthogonal-axis accelerometers located on the body thorax can be used to detect and characterize pathological gait. Moreover, motion is an important modulator of other vital human organic functions such as respiration, heart cycle, blood oxygen saturation and pressure. This paper focus on the automatic classification of human motion during daily activities.

In the state-of-the-art [3, 4, 5], off-line processing of acceleration data has been proposed: body acceleration information is recorded or transmitted as raw data and afterwards processed using an external platform. This approach presents important limitations when used in long-term monitoring platforms: either a long capacity data storage device or a broad bandwidth transmission system is required. In contrast to such off-line classification frameworks, the usage of an on-line approach allows storing directly activity classes rather than raw acceleration data leading to a decrease of storage or transmission requirements. Additionally, on-line activity classification can be used to develop new applications for portable devices (PDAs and mobile phones) aiming to provide live-training programs, interactive games and any other application related to activity monitoring. Consequently, the long-term and nomadic goals of this project urge for the need of low-power electronic and low-complexity digital signal processing to perform the prescribed activity classification task.

Such a daily monitoring of human activities supports the systematic medical analysis of data and offers a preventive alternative to care for cardio-vascular diseases and early diagnostic. The European Project MyHeart, started in 2003, is offering a unique platform for the development and assessment of such preventive medicine [6]. The acquisition of the accelerometer data, the development of the algorithmic part and the evaluation of the system performance are carried out in the context of the MyHeart European Project [6].

This paper presents an innovative solution for long-term nomadic monitoring and classification of a selection of daily activities, namely: walking, running, sitting, lying and walking upstairs/downstairs. The paper is organized as follows: Section presents the recording protocol, Section describes the features used to perform the classification, Section presents the classification strategy, Section deals with implementation issues and proposed solutions. Section presents and discuss the results, and finally Section concludes this paper.

Recording

The experimental set consists on a defined sequence of activities involving standing, walking, stairs walking and running performed by 10 subjects of different age ranges and sexes. In Table 1 some statistics on the temporal distribution of activities is provided: in average, each subject accomplishes 10 minutes of activity.

Table 1: Statistics on the activities being involved in the recordings

Activity	Volume in minutes	Percentage
Standing	13.8	13.3%
Walking	47.9	46.2%
Stairs Walking	33.3	32.1%
Running	4.4	4.2%
Others	4.3	4.2%
Total	103.7	100%

Recordings were performed using a CSEM portable data-acquisition platform. The platform records three-channel acceleration data with a sampling frequency of 25 Hz and 16 bits precision. Acceleration sensor consists of a 2x2D ADSXL accelerometer placed on a chest belt. The data is stored in a FLASH card and afterwards uploaded to a PC platform.

Features

The design of the features to be used in the classification machine must be done taking into account the final desired low complexity algorithm. For this reason, features derived from frequency or any other eigenfunction transformed domain have been eluded. A further study on the physiology of human motion has allowed the development of a new set of features derived from the temporal domain. In addition, only the data coming from the accelerometer acquiring vertical data has been used reducing by a factor of three the signal acquisition and processing complexity.

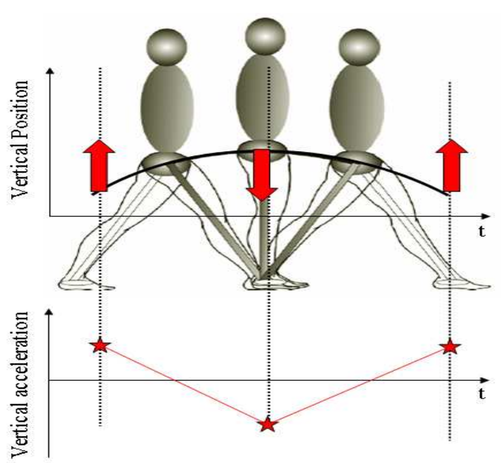

Figure 1: Spatial displacement of center of masses and consequent vertical acceleration pattern. Human image extracted from [7]

In [7] a good description of the kinematic of human walking is provided. According to this work, the mechanics of walking is defined as a *controlled falling* where the

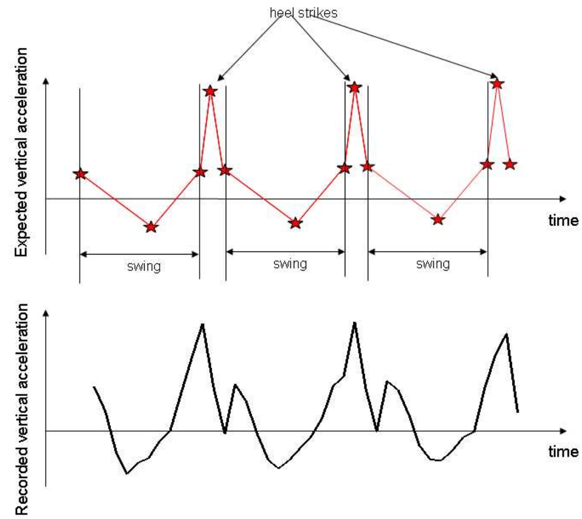

Figure 2: Expected vertical acceleration pattern according to the kinematic model and 1.6 seconds of real acceleration data acquired from a male adult

center of gravity oscillates over the supporting limb following an inverted pendulum movement (swing movement). Accepting such kinematic model, Figure **??** displays the spatial displacement of masses and the consequent vertical acceleration pattern. However, the model proposed by [7] does not include the consequences of heel strikes: at the end of each pendulum movement, the strike of the heel on the floor desaccelerates the swinging phase by generating an abrupt vertical acceleration. Consequently, Figure 2 illustrates the expected vertical acceleration derived from the extended walking model, together with real acceleration data corresponding to 1.6 seconds of an adult walking recording. Such kinematic model is analytically described by the following expression where n is the discrete time index and $\delta(n)$ is the discrete time Dirac distribution:

$$a(n) = \sum_i p(n) \otimes \delta(n - iT) \tag{1}$$

The convolution operator $\otimes$ has been used in (1). $\delta(n - iT)$ specifies the temporal position of each swing assuming a stationary period (T) and $p(n)$ describes a temporal pattern. The duration of such $p(n)$ is normally not longer than 500 ms and it is activity-dependent. Some examples of typical walking, stairs walking and running $p(n)$ are displayed in Figure 3.

Harmonical activity detection

In equation (1), the period T does not vary in time. Experimentally we observe that, in fact, T is time-dependent, i.e. $T = T(i)$. Following this observation, a continuous inspection of the temporal stationarity of $T(i)$ provides an estimation of the fitting to the kinematic model. A sliding standard deviation estimates of $T(i)$ accomplishes the estimation:

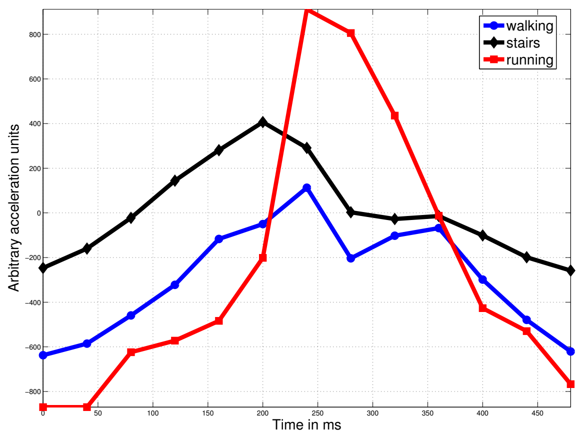

Figure 3: Temporal patterns $p(n)$ of swings for walking, stairs walking and running of a male adult.

$$h(i) = \sqrt{\frac{\sum_{j=i-L}^{i}(T(j) - \langle T_{i-L}\rangle)^2}{L}} \quad (2)$$

with $\langle T_{i-L}\rangle$ the time estimated average value of $T(k)$ for $k = i-L, \ldots i$. A database trained threshold on $h(i)$ determines the temporal borders in between harmonical activities.

Dynamic activity discrimination

The discrimination between dynamic activities (walking, stairs walking and running) is based on the analysis of $p(n)$. The zero crossings of a low passed version of $a(n)$ are used to localize and isolate two consecutive $p(n)$. For each $p(n)$ an energy estimation $e(i)$ and a feature $d(i)$ derived from the double integration of $p(n)$ determine a discriminative two dimensional feature space.

Static activities discrimination

Two static activities are planned to be distinguished: standing/sitting and lying. In this purpose the projection of the gravity vector over the vertical acceleration axis ($v(n)$) is estimated as a long memory averaging of $a(n)$. A data base trained threshold on such estimation has been determined.

Classification strategy

Being aware that different final applications require different classification resolutions, a decision tree is the most appropriate classification strategy. Depending on the desired complexity of the classification, it can be reduced to a basic activity/no activity classification, or leaf-extended to the four dimensional feature set. In Figure 4 the most extended topology of the decision tree is exposed and different degrees of refinement are displayed as basic classification, extended classification and full classification.

Implementation issues

As it has been already mentioned, the classification approach is based on a single acceleration channel corresponding to the subject's breast vertical axis. The algorithm has been implemented in a fixed-point LPC2106 (PHILIPS) 30MHz platform. In real time, the platform performs the data acquisition, feature extraction, classification and other signal processing routines as well (ECG and respiration monitoring).

In Figure 5 a block diagram summarizes the signal processing flow of data. The zero crossings of the low pass filtered acceleration $p(i)$ are used to compute the harmonicity $h(i)$ of the movement and to determine the borders in between two consecutive kinematics patterns. Together with the two features extracted from the kinematics pattern analysis, the projection of the gravity vector is introduced to the classification tree. The output of the system is an activity class tag which is provided each time a new step is detected.

Results

The behavior of the herein proposed approach has been tested using the database presented in Table 1 with the algorithms running offline. In order to evaluate the performance of the classifier, the database has been manually labeled. However, because of the short duration of some of the activities (specially in the running class and in the walking-stairs transitions) the evaluation of the goodness of the classificator is biased by the latency of the feature extraction (about 4 seconds). In the following table, the confusion matrix evaluated over the database is presented. In order to simplify the analysis, other and lying classes have been avoided from the matrix.

Table 2: Confusion matrix evaluated over the database. Rows depict real labeling and columns display classification outputs. Results are expressed in %

Activity	Resting	Walking	Stairs	Running
Resting	**87**	2	11	0
Walking	4	**70**	23	3
Stairs	5	10	**83**	1
Running	0	4	15	**81**

Assuming a balanced database (no apriori probability of the activities is taken in account) three overall scores can be evaluated (see Figure 4). In the basic classification case (activity/no activity) an overall score of 92% is obtained. In the extended classification case (no-activity, walking and running) the overall score is of 87% and

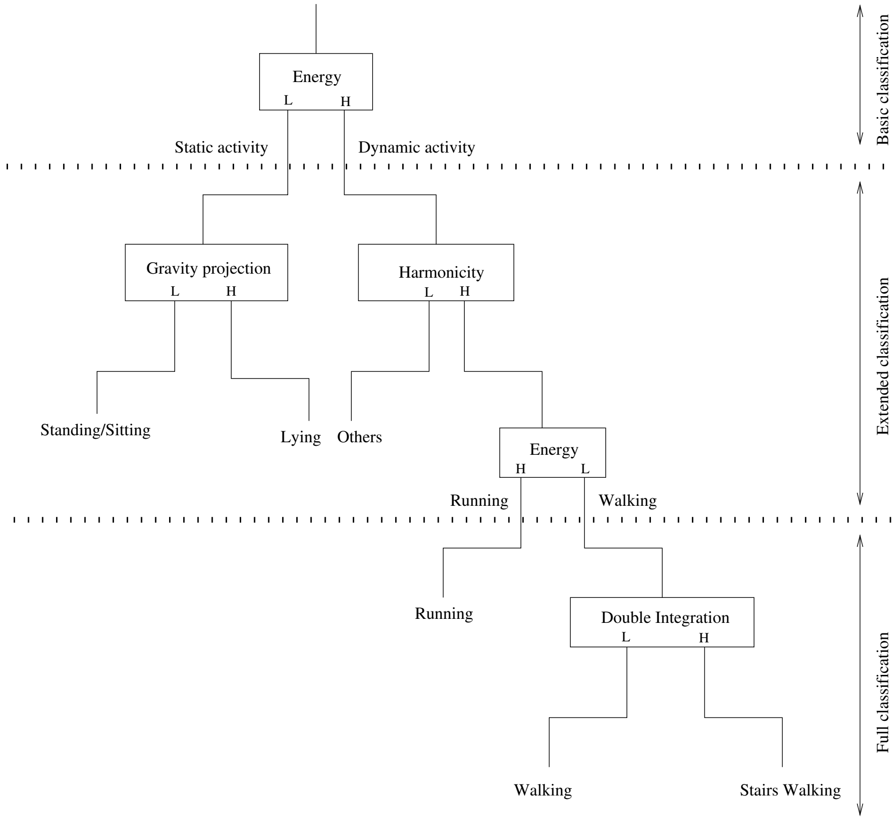

Figure 4: Complete topology of the decision tree.

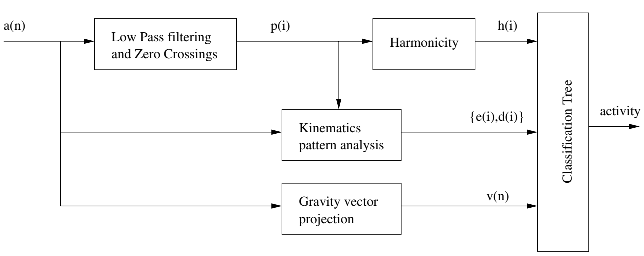

Figure 5: Complete block diagram of the signal processing data flow

in the full four classes classification paradigm an overall score of 80% is achieved.

Conclusion

We have presented an algorithm that performs human motion activity classification in 6 different classes. The algorithm has been designed in order to have the minimum complexity bearing in mind its implementation in a fixed-point limited resources platform such as the LPC2106. The algorithm was successfully implemented on this platform and evaluation tests are under way in the framework of the European MyHeart Project. Several applications are envisaged such as monitoring obese daily activities, post-surgery myocardial infarction patients, and depression/stress management. Tests are currently being undertaken by various hospitals in Europe.

References

[1] J. BERLIN and G.A. COLDITZ. A meta-analysis of physical activity in the prevention of coronary heart disease. *Am. J. Epidemiol.*, 132:612–628, 1990.

[2] U.S. DEPARTMENT OF HEALTH and HUMAN SERVICES. *Physical activity and health: a report of the Surgeon General*. U.S. Department of Health and Human Services, National Center for Chronic Disease Prevention and Health Promotion, 1996.

[3] M.J. MATHIE ET AL. Classification of basic daily movements using a triaxial accelerometer. *Medical & Biological Engineering & Computing*, 42:679–686, 2004.

[4] J. FAHRENBERG ET AL. Assessment of posture and motion by multichannel piezoresistive accelerometers recordings. *Psychophysiology*, 34:607–612, 1997.

[5] H.B. MENZ ET AL. Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. *Gait and Posture*, 18:35–46, 2003.

[6] MYHEART CONSORTIUM. Myheart project (IST-507816). *www.hitech-projects.com/euprojects/myheart*, 2003.

[7] R. GRASSO F. LACQUANATI and M. ZAGO. Mottor patterns in walking. *News Physiol. Sci.*, 14:168–174, 1999.