Application of a novel feature selector for human activity recognition based on inertial monitored data

Oresti Baños[1], **Miguel Damas**[1], **Héctor Pomares**[1], **Ignacio Rojas**[1] , **Beatriz Prieto**[1]

[1] Department of Computer Architecture and Computer Technology, University of Granada, C/Periodista Daniel Saucedo Aranda s/n E-18071, Granada, Spain

Abstract - *The last technological advances in wearable sensors and machine learning are allowing for a new generation of human monitoring techniques, with an especial interest for the analysis of human biomechanics and activity recognition. In this paper, an application of intelligent systems to solve the problem of daily physical activity recognition is presented. Taking into account the importance of data featuring and the selection of the most important features for subsequent pattern recognition stage, a new feature selection methodology based on a filter technique via a couple of two statistical criteria is presented. Satisfactory accuracy rates are achieved by using support vector machines especially for preprocessed data, with remarkable accuracy and applicability in the case of the wrist location.*

Keywords: Activity recognition, Feature selection, Ranking, Knowledge extraction, Support vector machines.

1 Introduction

An important research line is being focused on the monitoring of human biomechanics by using different sensor and methodologies. One of the most important topics in this issue is automatic physical activity recognition, with an increasingly outcome in healthcare related applications, particularly centered on the aged people [15]. Supporting a more independent life and mobility for the elderly, improving their welfare and health status and facilitating more autonomous activities regardless the location is one the most important objectives of this kind of applications.

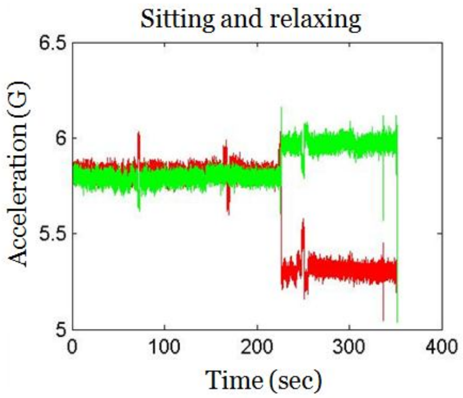
Vision [9, 12], microphones [13] or ambient sensors [6] are widely used, but attending for the simplicity and the capabilities of the new generation of mobile systems, inertial sensors have been considered as the most interesting approach. In this work we present a particular methodology stressing on feature selection stage to extract a set of the most important features to be used in activity recognition, considered extremely important to ensure the performance of the subsequent pattern recognition system employed. One of the most important characteristic of the method proposed is that we do not provide a rank order for every individual feature but for every set of features, allowing for the synergic utility of several features when considered together at the same time.

The rest of the paper is organized as follows: In Section 2 a brief summary of the experimental setup and the data preprocessing is made. Next, the rank-based feature-set selection methodology developed is presented, describing the fundamentals of this method and the algorithm's main steps. Section 4 presents the results obtained for the performance of the method for a specific example, comparing the accuracy results with related previous works.

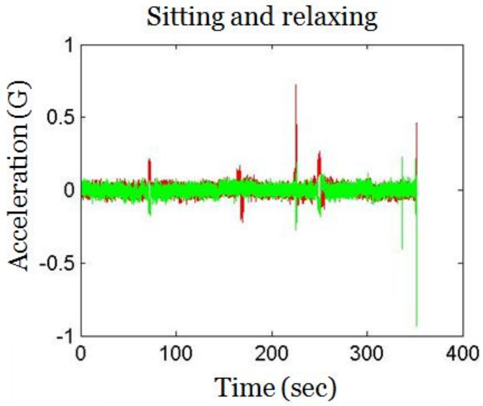
2 Data processing and featuring

The initial setup starts from a signal set corresponding to acceleration values measured by a group of sensors located in strategic different parts of the body (hip, wrist, arm, ankle, thigh), for four daily activities (walking, sitting, standing, running) [1].

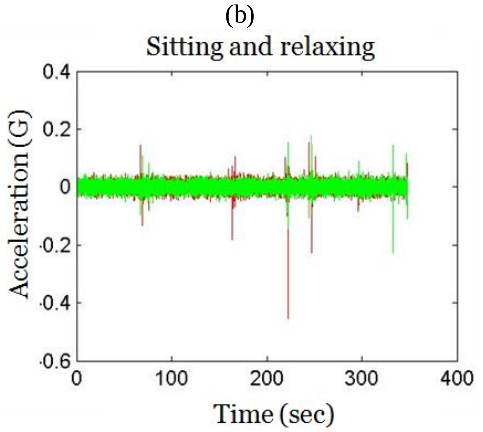
Distortion elements related to system monitoring and processing, along with the random character of the individual execution determine that a particular data processing and analysis should be done. One goal of this work is to evaluate the importance of this preprocessing stage. It is well-known that filtering techniques normally entail loss information, so it would be interesting to compare the results in contrast to work directly with the original raw signals. According to this, two processing techniques are respectively tested, consisting of a mean filter (Fig. 1.b) and a band pass filter (Fig. 1.c). The mean filtering is defined to remove the initial offset introduced in the original data acquired and the discontinuities associated to the sensors calibration changes between different monitoring sessions (Fig. 1.a). Band pass filtering also permits to remove the high frequency noise. Considering that a 20 Hz sampling is sufficient to assess habitual daily physical activity [8], an elliptic filter with 0.5Hz and 20 Hz cutoff frequencies is used for the last one.



(a)



(b)



(c)

Figure 1. Signals (green = x-axis, red = y-axis) corresponding to the activity 'sitting and relaxing', monitored through the wrist accelerometer. a) Original data with a 5.8G offset and a discontinuity at second 220 approx., b) Mean filtered data and c) BP filtered data.

Once data have been processed, a parameter set made up of 861 features corresponding to a combination of statistical functions such as mean, kurtosis, mode, variance, etc., and magnitudes obtained from a domain transformation of the original data such as energy spectral density, spectral coherence or wavelet decomposition, among others. These features are evaluated over the complete signal, although other alternatives based on windowing and sub-segmentation signal feature extraction could also been tested.

In this stage, we now must rely on a feature selection process that has the responsibility of deciding which features or magnitudes are the most important ones to decide the kind of activity the person is carrying out. In the next section we describe the method we have designed to accomplish this task.

3 Feature selection based on discrimination and robustness statistical criteria

To obtain a specific group of variables from a big initial set is not a trivial task because of the huge number of possible feature combinations. In our experimental setup the sample space is represented by n = 861 features, so brute force techniques like 'branch and bound' (O(2n) convergence □ 2861 ≈ 1.5 x 10259 possible permutations) or wrapper methods are impractical. In this section, we present an alternative method based on the concepts of discrimination and robustness for a complete set of features.

Let us define the sample range of a class as the set of values included between the maximum and the minimum value (both inclusive) that a feature or variable takes for this class. Given a group of samples (associated to every class) we rank its discriminant capability with respect to that class through the overlapping probability between this class and the others. This is calculated computing the number of samples from the analyzed class which are inside of the sample range defined by the others. For N classes and M samples for each class (let us suppose that this number is independent of the class), we define the overlapping probability of a set of samples as follows:

$$p(k)=\frac{1}{N-1}\sum_{n\neq k}^{N}\frac{m(k,n)}{M} \qquad (1)$$

with *m(k,n)* being the number of samples from the class *k* inside the sample range of class *n*.

We now carry out a thresholding process which allows us to define the feature analyzed as discriminative or not. This *overlapping* threshold takes values from 0 (the most restrictive, for cases with no overlapping between classes) to 1 (the most relaxed, when every sample from a class is inside the others). In general for a specific feature, if the analyzed class exceeds the threshold, the feature will be considered as no discriminant for this class.

Table 1. Example for 4 classes and 5 sources of quality feature set (ranking) based on discriminant (number of activities discriminated, first column) and robustness (number of motion sensor where the feature is discriminant, second column) criterions.

Discriminant capacity	Robustness	Quality group
4	5	#1
	4	#2
	3	#3
	2	#4
	1	#5
3	5	#6
	4	#7
	3	#8
	2	#9
	1	#10
2	5	#11
	4	#12
	3	#13
	2	#14
	1	#15
1	5	#16
	4	#17
	3	#18
	2	#19
	1	#20
0	-	#21

Apart from the discriminant capacity of a feature or a set of features, a second characteristic is now defined which takes into account the usability of this set of features in different information contexts or sources. For instance, a specific measure taken from the hip accelerometer can be very discriminative to distinguish between the activities *walking* and *standing still*, but this very same measure may not be that reliable when taken from the ankle accelerometer.

There may be some measures with the same discriminant capability between those activities which are not so dependent of the exact location of the sensor or, at least, which are still reliable when taken from a bigger number of sensors. We will denote this measure as the robustness criterion of a set of features. In short, discriminant capacity says how useful a motion feature is in general, and robustness is how this depends on where the sensor is.

Combining both criteria we obtain a quality ranking procedure capable of grouping features in different stages. For the sake of simplicity, let us suppose a recognition system with 4 classes and 5 sources; features will be classified in groups defining a ranking (see table 1). For instance, features that discriminate 4 classes in every source will be added to group #1 (the best). Group #13 will be completed with features that classify 2 classes (the same) in 3 sources at least. This example is extensible to any classes and sources.

4 Results

Most remarkable features (set #1 and #2 primarily) are geometric mean for amplitude signal, autocorrelation and some wavelets coefficients obtained through a 3-level Daubechies decomposition. For classification paradigm, taking into account the good results obtained in several machine learning previous works, and even not being much used in activity recognition studies related, the knowledge inference system is defined through support vector machines (SVM) [11], using a RBF kernel implementation with hyper-parameters γ and C automatically tuned using a grid search. A 10-fold cross validation method is used for training and testing. Results are showed in Figure 2.

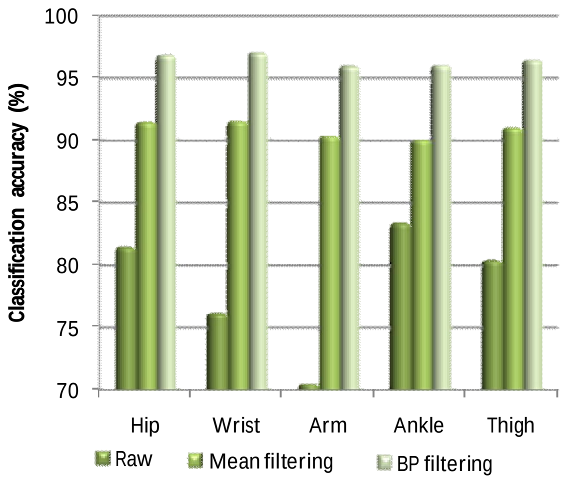


Figure 2. Accuracy rates for the three processing approaches. Results are identified with the corresponding sensor label depending on the location of the source data.

Clearly, the preprocessing is needed to optimize the recognition capability of the system, with particular remarkable results for the band pass (BP) approach. In fact, the mean filtering, that could be reasonably interpreted as a low pass filter (to remove the DC bias or 0Hz component) determines an important improvement from the unprocessed data. Notwithstanding, the BP filter also permits the removal of the frequency components above 20Hz. This demonstrates that there are irregularities and abnormalities in upper frequencies that make more difficult the discrimination task, at least for the four activities analyzed.

Besides good results are obtained in general for the BP filtering approach, we want to stress on the importance that these results are achieved for each sensor separately, it means, no information from other sensors is needed to

accomplish the activity recognition task. Considering that accuracy rates above 95% for all the sensors any studied placement will work efficiently for the activities analyzed, but particularly interesting is considered the wrist sensor location because of the highest experimental accuracy (>97%) and especially for its unobtrusive properties.
Although a strict comparison with other studies cannot be made since the data and the number of classes may differ, in [7] a 83-90% classification accuracy was reached, 92.85%-95.91% in [5], 89% in [1], or 93% and 89% on recent works ([2] and [3] respectively).

5 Conclusions

In this work we have very briefly shown a direct application of ranking selection methods used on daily physical activity automatic recognition. An efficient classification method requires a productive and limited feature set, being necessary a selection process since the initial set is quite huge. We have defined a feature selector based on statistical discrimination and robustness criteria, focused on low computational time and resources, defining a real alternative to other selection processes.

The importance of an adequate preprocessing stage has been also showed, demonstrating that singularities and irregularities affect physical activity monitored data. The wrist location stands out for its efficiency and unobtrusively.

For future work, we aim to make a time-based comparison to traditional features selectors [4,10,14].

6 Acknowledgments

This work was supported in part by the Spanish CICYT Project TIN2007-60587, Junta de Andalucia Projects P07-TIC-02768 and P07-TIC-02906, the CENIT project AmIVital, of the "Centro para el Desarrollo Tecnológico Industrial" (CDTI- Spain), the FPU Spanish grant AP2009-2244 and the UGR grant "Iniciación a la Investigación 2010/2011". We want to express our gratitude to Prof. Stephen S. Intille, Technology Director of the House_n Consortium in the MIT Department of Architecture for the experimental data provided.

7 References

[1] Bao, L., Intille, S.S.: Activity Recognition from User-Annotated Acceleration Data. In: Activity Recognition (Pervasive Computing) ». LNCS, vol. 3001, pp. 1--17. Springer, Heidelberg. (2004)

[2] Bonomi, A.G., Goris, A.H.C., Yin, B., Westerterp, K. R.: “Detection of Type, Duration, and Intensity of Physical Activity Using an Accelerometer”. Medicine & Science in Sports & Exercise. vol. 41, pp. 1770--1777. (2009)

[3] Ermes, M., Pärkka, J., Mantyjarvi, J., Korhonen, I.: “Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions”. IEEE Trans. Inf. Technol. Biomed. vol. 12, pp. 20--26. (2008)

[4] Kohavi, R., Sommereld, D.: “Feature Subset Selection Using the Wrapper Method: Overtting and Dynamic Search Space Topology”. First International Conference on Knowledge Discovery and Data Mining (1995)

[5] Lee, S.W., Mase, K.: Activity and location recognition using wearable sensors. IEEE Pervasive Computing. vol. 1, pp. 24--32. (2002)

[6] Logan, B., Healey, J., Philipose, M., Tapia, E.M., Intille, S. S.: “A long-term evaluation of sensing modalities for activity recognition”. In: Proceedings of the 9th international conference on Ubiquitous computing, pp. 483--500 (2007)

[7] Mantyjarvi, J., Himberg, J., Seppanen, T.: “Recognizing human motion with multiple acceleration sensors”. In: Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, pp. 747--752. (2001)

[8] Mathie, M.J., Coster, A.C.F., Lovell, N.H., Celler, B.G.: “Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement”. In: Physiol. Meas., vol. 25, pp. 1--20. (2004)

[9] Ryoo, M.S., Aggarwal, J.K., Patras, I.: “Semantic representation and recognition of continued and recursive human activities”. In: International Journal of Computer Vision, vol. 82, pp. 1--24. (2009)

[10] Song, L., Smola, A., Gretton, A., Borgwardt, K.M., Bedo, J.: “Supervised feature selection via dependence estimation”. In: Proceedings of the 24th international conference on Machine learning, pp. 823--830. (2007)

[11] Vapnik, V. “Statistical Learning Theory”, John Wiley & Sons. (1998)

[12] Wang, Z., Li, B.: “Human activity encoding and recognition using low-level visual features”. In: Proceedings of the 21th International Joint Conference on Artificial Intelligence, pp. 1876--1882. (2009)

[13] Ward, J., Lukowicz, P., Troster, G., Starner, T.: “Activity Recognition of Assembly Tasks Using Body-Worn Microphones and Accelerometers. Pattern Analysis and Machine Intelligence », IEEE Transactions on, vol. 28, pp. 1553--1567. (2006)

[14] Xu, Z., Jin, R., Ye, J., Lyu, M.R., King, I.: “Non-monotonic feature selection”. In: Proceedings of the 26th Annual International Conference on Machine Learning, pp. 1145--1152. (2009)

[15] Yu, X.: “Approaches and principles of fall detection for elderly and patient. In: e-health Networking”, Applications and Services, 2008. HealthCom 2008. 10th International Conference on, pp. 42--47. (2008)