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Recognition of Human Physical Activity based on a novel Hierarchical Weighted Classification scheme

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***Abstract*—The automatic recognition of postures, movements and physical exercises has being recently applied to several healthcare related fields, with a special interest in chronic disease management and prevention. In this work we describe a complete method to define an accurate activity recognition system, stressing on the classification stage. As binary classifiers can be, in general, considered more efficient than direct multiclass classifiers, and looking for an appropriate multiclass extension schema, a hierarchical weighted classification model with a special application for multi-sensed problems is presented. Remarkable accuracy results are obtained for a particular activity recognition problem in contrast to a traditional multiclass majority voting algorithm.**

I. Introduction

CHRONIC non-communicable diseases (CNCDs) - principally cardiovascular diseases, cancer, and diabetes - are the leading causes of premature death and disability in most American countries, accounting for 60%–70% of all deaths in the Region [16]. These diseases share common risk factors which include tobacco use, physical inactivity, obesity and hypertension (high blood pressure). There is sufficient evidence that CNCDs can be prevented and controlled through changes in lifestyle, public policies and health interventions. If these risk factors were eliminated at least 80% of all heart diseases, strokes and type 2 diabetes and over 40% of cancer cases could be prevented [15].

The considerable research effort directed toward monitoring and classification of physical activity patterns from body-fixed sensor information may aid to establish proactive conducts based on a subject-specialized personal status control. Works centered on the measurement of energy expenditure [3,5], analysis of the common activities and habits carried out on the daily living [8,11] or the combination of both [13] are revealing the possibilities offered by inertial monitoring systems in CNCDs prevention [14].

One of the most important stages on activity recognition systems is machine learning. Several paradigms such as artificial neural networks [8], support vector machines [10], Bayesian classifiers [2] or hidden Markov models [12] have been widely used, but they are less accurate as the number of classes (activities) grows [9].

Some of these schemas are originally defined through binary classification, recognized as the most interesting approach [1], but in some cases traditional multiclass generalization is not efficiently practical [6]. Besides, the use of several inertial monitoring systems usually improves the system accuracy rates, but to the best of our knowledge, no general models are presented for the combined use of them. We here propose a wide-ranging multiclass scheme by reducing the study to multiple binary or class specialized problems, employing a weighted structure to define the decision maker. This scheme is extended to each information source to define a hierarchical knowledge inference system with a two-level weighting decision framework.

The rest of the paper is organized as follows. In section 2 a brief summary of the activity recognition process is presented. Section 3 describes the hierarchical weighted classification methodology proposed, showing the fundamentals of this method and the algorithm's main steps. Finally the performance of the method is evaluated for a specific example in section 4.

II. Activity Recognition Method

The experimental setup starts from a signal set [2] corresponding to acceleration values measured by a group of sensors located in several strategic body locations (hip, wrist, arm, ankle, thigh), for eight daily activities (walking, sitting and relaxing, standing still, running, bicycling, lying down, brushing teeth, climbing stairs). The methodology presented from this point forward can be easily generalized to other studies related to activity recognition from a set of features.

Monitored data have some artifacts and noise associated to the acquisition data process. Consequently a band pass filtering (0.5Hz to 20Hz) is used to remove these irregularities.

A parameter set made up of 861 features is subsequently obtained. This corresponds to a combination of statistical functions such as mode, median, variance, etc., and magnitudes obtained from a domain transformation of the original data such as energy spectral density, spectral coherence or wavelet decomposition ("a1 to a5" and "d1 to d5" Daubechies levels of decomposition), among others. The complete set is shown in Table 1.

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TABLE I
FEATURE SET GENERATION FUNCTIONS

Magnitudes	Statistical functions
Amplitude	4^{th} and 5^{th} central statistical moments
Autocorrelation function	Energy
Cepstrum	Arithmetic/Harmonic/Geometric/ Trimmed mean
Cross correlation function	Entropy
Energy spectral density	Fisher asymmetry coefficient
Spectral coherence	Maximum / Position of
Spectrum amplitude/phase	Median
Histogram	Minimum / Position of
Historical Data Lags	Mode
Minimum phase reconstruction	Kurtosis
Daubechies wavelet decomposition	Data range
	Total harmonic deviation
	Variance
	Zero crossing counts

The feature selection process has the responsibility of deciding which features or magnitudes are the most important ones to infer the kind of activity the person is carrying out. In this paper, a feature selector based on the Mann-Whitney-Wilcoxon test is employed [7].

III. Hierarchical Weighted Classifier (HWC)

Concerning the classification stage, it is extremely important to establish an appropriate multiclass extension scheme to preserve and optimize binary entities capabilities, especially when fusion of several sensors or sources is considered. A general method based on the combination of binary or multi-class classifier decisions in a hierarchical structure with a special application for multisource problems is presented in this section.

The proposed Hierarchical Weighted Classifier (HWC) is composed by three classification levels or stages (see Fig. 2). In general, for M sources of information and N classes, a set of M x N "class classifiers" (c_{mn}) are defined. They are binary classifiers specialized in the classification of the class n by using the data acquired from the m-*th* source. Each one applies an *one-versus-rest* strategy, so any classification paradigm can be easily used. These define the base level or *class level classifier*. The second stage, *source level classifier*, is defined by M "source classifiers" (S_m). Source classifiers are not machine learning-type classifiers, but hierarchical decision models which define a classification entity. Source classifiers structures are composed by several class classifiers as is shown in Fig. 2, defining a decision system based on weighted decisions of class classifiers. This approach is repeated for the next level, *method level classifier*, which ultimately defines a decision structure constituted by weighted decisions of source classifiers.

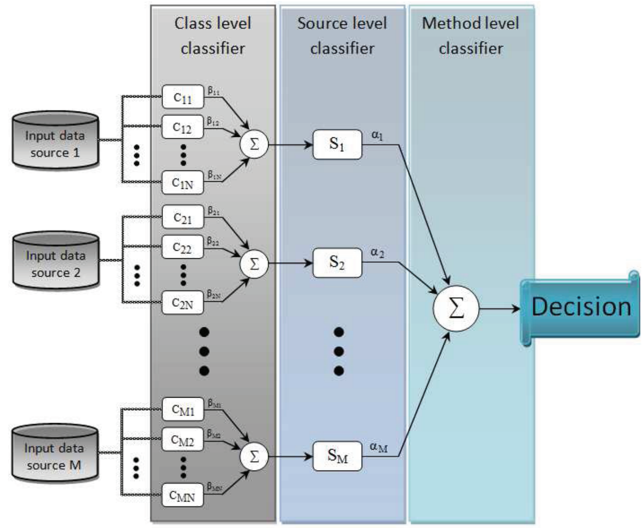

Fig. 2. HWC general structure for a problem with N classes and M sources.

In accordance to the structure described above, a process consisting of a few main steps is carried out to define the complete HWC. The process starts by evaluating the individual accuracy of each class classifier, defined through its corresponding feature vector (several vector lengths should be considered to find out the best results for every classifier). A 10-fold cross validation is suggested for accomplish this task and this is repeated to ensure statistical robustness (for example 100 times). This whole process is repeated for each source. Considering average accuracy rates ($\overline{R_{mn}}$ for source m and class classifier n) as a measure of the pattern recognition capabilities of each classifier, an associated weight is obtained for each one:

$$\beta_{mn} = \frac{\overline{R_{mn}}}{\sum_{k=1}^{N} \overline{R_{mk}}} \tag{1}$$

These weights are a measure of the importance that every class classifier will have on the source classifier decision scheme. A specific voting algorithm is considered at this stage to obtain the final decision of the source classifiers. For a source m, given a sample x_{mk} to be classified and being q the class predicted by the classifier c_{mn}, if the sample is classified as belonging to the classifier class of specialization (q=n), the classifier will set its decision as '1' for the class n and '0' for the rest of classes. The opposite is made for (q≠n). In summary, the decision from the classifier n for the class q (q,n=1,...,N) is:

$$D_{nq}(x_{mk}) = \begin{cases} 1, & x_{mk} \text{ classified as } q \\ 0, & x_{mk} \text{ not classified as } q \end{cases} \; \forall q = n \qquad \begin{cases} 1, & x_{mk} \text{ not classified as } q \\ 0, & x_{mk} \text{ classified as } q \end{cases} \; \forall q \neq n \tag{2}$$

Once the decisions have been made by each class classifier for every class q by applying (2), it is time to compute the weighted output for the *m-th* source classifier:

$$O_{mq}\left(x_{mk}\right)=\sum_{n=1}^{N}\beta_{mn}D_{nq}\left(x_{mk}\right) \qquad (3)$$

Finally, the class predicted for the *m-th* source classifier (q_m) is the class q for which source classifier output is maximized:

$$q_{m}=\arg\max_{q}\left(O_{mq}(x_{mk})\right) \qquad (4)$$

At this stage, the source level classifier is completely defined. Every source class classifier can be used separately. If very accurate classifiers are found, maybe this is enough to be used as the final solution of the pattern recognition system. However, fusion or combination of sources information is in general a more robust and efficient solution. Consequently, the complete process described before is extended to a new hierarchy level, the method level classifier. First, source classifiers weights (α_m) are obtained by calculating the average accuracy rates for each source classifier ($\overline{R_m}$), so a cross-validation process is again repeated but now focusing on the source classifiers' predictions. The weight for the source m is:

$$\alpha_{m}=\frac{\overline{R_{m}}}{\sum_{k=1}^{M}\overline{R_{k}}} \qquad (5)$$

The output is calculated taking into account the individual outputs obtained for each source classifier. For a sample x_k defined through the corresponding information obtained from each source ($x_{1k},\ldots,x_{Mk}$):

$$O_{q}(x_{k})=O_{q}(\{x_{1k},\ldots,x_{Mk}\})=\sum_{p=1}^{M}\alpha_{p}O_{pq}(x_{pk}) \qquad (6)$$

Similar to (4) the final class predicted q is:

$$q=\arg\max_{q}\left(O_{q}(x_{k})\right) \qquad (7)$$

In summary, the HWC is absolutely defined through the class classifiers (c_{mn}), class level weights (β_{mn}) and the source level weights (α_m) at this point.

IV. RESULTS

The aim of the methodology presented is to define robust and efficient pattern recognition systems based on binary class classifiers. For the activity recognition problem presented (N = 8, M = 5), two classification schemas based on majority voting (MV) and our approach (HWC) are respectively used. Naive bayes machine learning paradigm is employed as machine learning structure for the class classifiers, using the first one (Fig. 3.a) and the first ten (Fig. 3.b) best features selected (for every source and class).

Results obtained for the MV approach are significantly improved by using the HWC, up to nearly 10% in some cases as *hip* source (Fig. 3.a) or *thigh* accelerometer (Fig. 3.b). This is extensible to *fusion* of source classifiers or *method level classification*. In fact, no improvement is achieved for *fusion* approach when is used following a MV scheme, with results in line to the most accurate source level classifier (~80%, as *arm* source classifier when 1 feature is used, and ~93%, as *wrist* source classifier when 10 features are used). Conversely, an important enhancement is obtained for HWC, particularly notable for the case of using 1 solely feature, achieving an average accuracy rate of 98%, that represents more than 10% to the best source classifier for the same model, and up to 15% with respect to the MV fusion approach.

Accuracy differences seem to be less abrupt between HWC and MV when more features are used, obtaining better source classifiers for both models. This is because more

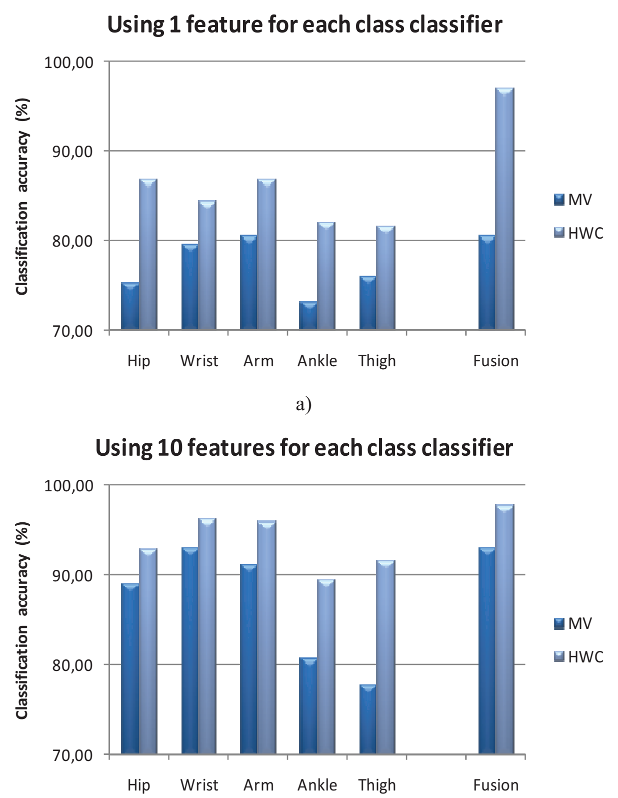

Fig. 3. Accuracy rates using MV and HWC schemas respectively. Results for each source classifier are identified with the corresponding sensor label. Fusion is referred to the combined use of the different source classifiers (identified as *method level classifier* in section III).

TABLE II
DETAILED ACTIVITY-RECOGNITION RESULTS OF THE 1 FEATURE BASED HWC BY USING THE FUSION APPROACH

		Predicted class								
		Walking	Sitting and relaxing	Standing still	Running	Bicycling	Lying down	Brushing teeth	Climbing stairs	*Class-specific recall*
Actual class	Walking	95,33	0,00	0,00	0,00	0,00	0,00	0,00	0,00	***1,00***
	Sitting and relaxing	0,00	99,83	0,00	0,00	0,00	12,33	0,00	0,00	***0,89***
	Standing still	0,00	0,00	99,83	0,00	0,00	0,50	0,00	0,00	***1,00***
	Running	3,67	0,00	0,17	100,00	0,00	0,00	0,00	5,50	***0,91***
	Bicycling	0,00	0,00	0,00	0,00	100,00	0,00	0,00	0,00	***1,00***
	Lying down	0,00	0,00	0,00	0,00	0,00	87,17	0,00	0,00	***1,00***
	Brushing teeth	0,17	0,17	0,00	0,00	0,00	0,00	100,00	0,00	***1,00***
	Climbing stairs	0,83	0,00	0,00	0,00	0,00	0,00	0,00	94,50	***0,99***
	Class-specific precision	***0,95***	***1,00***	***1,00***	***1,00***	***1,00***	***0,87***	***1,00***	***0,95***	

efficient and robust class classifiers are achieved, so importance of decision makers is smaller amount. The use of a larger feature set to define the inference systems implies that more computational requirements are necessary, an important issue in real time activity recognition systems. Notwithstanding, technical simplified solutions should be considered, bearing in mind the importance of unobtrusiveness in wearable monitoring contexts. Consequently, a trade-off must be reached between the unobtrusively condition and the computational and real-time requirements of end-user-oriented systems. In our case, some source classifiers as the wrist or the arm related accelerometer placement offer remarkable results (~96%) for the HWC approach, defining two possible solutions for the activity recognition problem.

The example above allows us to better understand the optimization capabilities of the hierarchical weighted scheme presented. Average accuracy results for HWC fusion approach are approximately the same independently of the feature vector size. In this case, applying the fusion approach and considering the computational resources requirements, 1 feature based models would be preferred instead of 10 features approach, showing table II the average results obtained for each class separately. High accuracy results close to 100% are obtained for the major activities, except for *walking* and *climbing stairs* activities with approximately a 95% ratio, primarily confused with *running*, and *lying down* with more than 87%, that is sometimes interpreted as *sitting and relaxing* or *standing still*, similar sedentary activities. Regardless, the results obtained for this fusion approach are particularly remarkable considering the significant lower accuracy rates obtained for each source level classifier.

V. CONCLUSION

Several advantages are obtained to traditional multiclass schemas as majority voting. Primarily only features with high binary discriminant capacity are required because of class specialized classifiers define completely the knowledge base of the model. This reduces the complexity of feature selection processes. Besides, once source and class level weights are calculated for the corresponding problem analyzed, the classification system is simply defined through a few decision rules that are easily extended from source classifiers to the complete hierarchy.

The first hierarchy level for both models is composed by the same binary class classifiers. Despite of this, significant differences have been obtained by comparing MV and HWC approaches, demonstrating the usefulness of our weighted schema. A simple activity recognition system has been defined by using solely one feature for each class classifier with accuracy rates close to 100% for fusion approach. Increasing complexity of the source classifiers (it means, by using more features), results are particularly remarkable for the first level of the hierarchy defined (source classifier), having outstanding accuracy rates for some specific sensors as the wrist, so interesting for the unobtrusively and applicability of wearable monitoring activity recognition systems.

The good results obtained for the example above are promising for applying this technique to a problem with more classes. For future work we want to test our methodology in different problems related or others (*UCI repository* [4]) with a spread range of classes.

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