Human multisource activity recognition for AAL problems

Oresti Banos, Miguel Damas, Hector Pomares, Ignacio Rojas

***Abstract*—The recognition of simple human biomechanical actions as postures or movements, or more complex behaviors as exercises or activities is attracting much research in recent years. The difficulty of the problem due to the diversity of activities and the individuals' particular execution style determines that several information sources are usually required to obtain an efficient solution, with more sources to be considered as the number of activities increases. One of the main goals is to define an accurate system which is able to deal with several information sources, with classification process as one of the most crucial parts. Considering the power of binary classification in contrast to direct multiclass approaches, a novel classification schema based on a hierarchical structure composed by weighted decision makers is defined. Satisfactory performance is obtained for a particular activity recognition problem in contrast to a traditional hierarchical multiclass model.**

I. Introduction

THE enhancement of the quality of life of the elderly is one of the most important goals considered in the ambient assisted living (AAL) framework. For this purpose, the main idea is to reduce the innovation barriers of forthcoming promising markets, and to lower future social security costs through the use of the potential offered by the information and communication technologies (ICT). The motivation of this new funding activity is in the demographic change and ageing in Europe, which implies not only challenges but also opportunities for the citizens, the social and healthcare systems as well as industry and market.

In this context, the monitoring and recognition of daily living activities is significant, with a particular research effort directed to wearable sensor based systems. Chronic disease management [12], rehabilitation systems [8] or disease prevention [11] are several topics where activity recognition potential is being revealed.

One of the most important stages on activity recognition systems is machine learning. Several paradigms such as artificial neural networks [6], support vector machines [8], Bayesian classifiers [3] or hidden Markov models [9] have been widely used, but they are less accurate as the number of classes (activities) grows [7].

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Considering binary classification more accurate in general than direct multiclass approaches, it is extremely important to establish an appropriate multiclass extension scheme which permits to preserve binary entities capabilities. Besides, potential of source fusion understood as the use of information registered by multiple homogenous/heterogeneous sensors is not always properly used. A general methodology is presented in this section based on the combination of binary or class classifier decision makers on a hierarchical structure defined with a special interest for multisource problems.

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 [3] 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 (see Fig. 1). The methodology presented from this point forward can be easily generalized to other studies related to activity

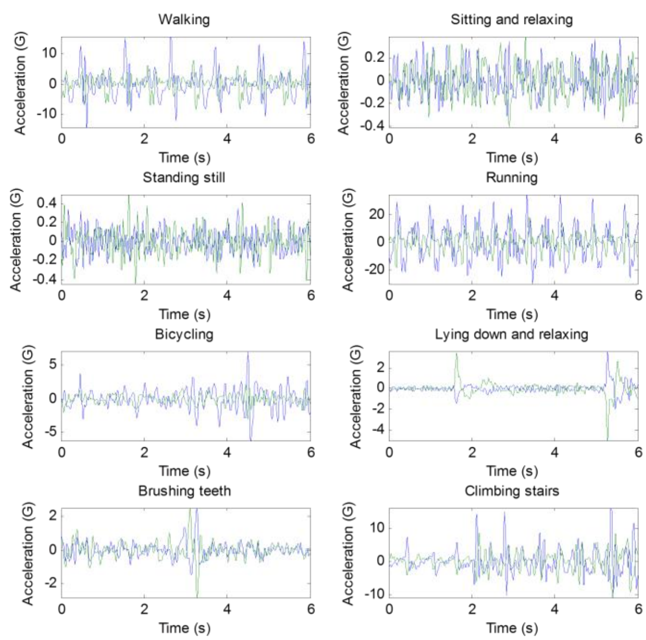

Fig. 1. Signals corresponding to eight usual daily physical activities (hip accelerometer). X axis in blue, Y axis in green respectively.

recognition from a set of features.

Monitored data have some artifacts and noise associated to the acquisition data process. Considering that a 20 Hz sampling is sufficient to assess habitual daily physical activity [5], a low pass elliptic filter with 20 Hz cutoff frequency, followed by a 0.5 Hz cutoff frequency high pass elliptic filter (both 0.5dB passband ripple and 20dB stopband attenuation) are applied to respectively remove the high frequency noise and the original signal offset.

Afterward a parameter set made up of 2583 features is 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 ("a1 to a5" and "d1 to d5" Daubechies levels of decomposition) among others for both signal axes. "Fisher asymmetry coefficient of the X axis signal histogram", "Y axis signal wavelet coefficients a2 zero crossing counts" or "X axis-Y axis cross correlation harmonic mean" are possible examples of features obtained from the set defined [2].

Feature selection processes have the responsibility of deciding which features or magnitudes are the most important ones to infer the kind of activity the person is carrying out. Taking into account the binary class classifier approach (described in the next section), several class specialized feature selection schemas based on an 'one-against-all' strategy have been applied to the data. In this paper, a feature selector based on the receiver operating characteristic (ROC) is employed [10].

III. Hierarchical Weighted Classifier (HWC)

Considering binary classification in general more accurate than direct multiclass approach, is extremely important to establish an appropriate multiclass extension schema which permits to preserve and optimize binary entities capabilities, even more when fusion of several sensors or sources is considered. A general methodology based on the combination of binary or class classifier decisions in a hierarchical structure with an special application for multisource problems is presented in this section.

The framework of the HWC is composed by three classification levels or stages related to the decision structure defined (see Fig. 2). In general, for $m=1,...,M$ sources and $n=1,...,N$ 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 source. Each one applies an 'one-versus-rest' strategy, so any classification paradigm can be easily applied. These define the first 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 as class 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 class classifiers weighted decisions. This approach is repeated for the next level, *method level classifier*, which ultimately defines a decision structure constituted by source classifiers weighted decisions.

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 100 times to ensure the statistical robustness. The entirely 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:

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

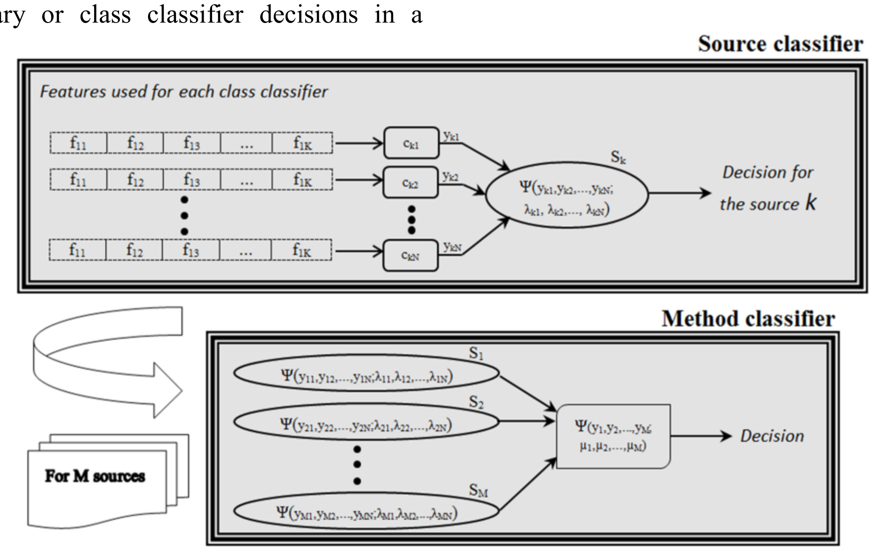

Fig. 2. HWC general structure for a problem with N classes and M sources.

These weights are a measure of the importance that every class classifier will have on the source classifier decision schema. A specific voting algorithm is considered in this point to define source classifiers decision. 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 specia lization ($q=n$), the classifier will set its decision as '1' for the class n and '0' for the rest of classes. Opposite is made for ($q\neq n$). In summary, the decision from the classifier n for the class q is:

$$y_{nq}(x_{mk})=\begin{cases}\left.\begin{array}{ll}1, & x_{mk}\ \mathit{classified\ \ as}\ q\\ 0, & x_{mk}\ \mathit{not\ classified\ \ as}\ q\end{array}\right\} & \forall q=n\\ \left.\begin{array}{ll}1, & x_{mk}\ \mathit{not\ classified\ \ as}\ q\\ 0, & x_{mk}\ \mathit{classified\ \ as}\ q\end{array}\right\} & \forall q\neq n\end{cases} \qquad (2)$$

Once decisions have been offered by each class classifier for every class q by applying (2), it is time to compute the weighted output for the m source classifier. In this case, a cumulative sum linear function is considered for Ψ:

$$O_{mq}(x_{mk})=\Psi\left(\lambda_{mn}y_{nq}(x_{mk})\right)=\sum_{n=1}^{N}\lambda_{mn}y_{nq}(x_{mk}) \qquad \forall q=1,\ldots,N \qquad (3)$$

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

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

Here, the source level classifier is completely defined. Every source class classifier can be used separately, looking for the most interesting for the particular problem analyzed. If extremely accurate classifiers are found, maybe this is enough to be used as the final pattern recognition system solution. 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 (μ_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:

$$\mu_m=\frac{\overline{R_m}}{\sum_{k=1}^{M}\overline{R_k}} \qquad (5)$$

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

$$O_q(x_k)=O_q(\{x_{1k},\ldots,x_{Mk}\})=\Psi\left(\mu_pO_{pq}(x_{pk})\right)=\sum_{p=1}^{M}\mu_pO_{pq}(x_{pk}) \qquad \forall q=1,\ldots,N \qquad (6)$$

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 (λ_{mn}) and the source level weights (μ_m) at this point.

IV. Results

For the activity recognition problem presented two classification schemas based on traditional hierarchical

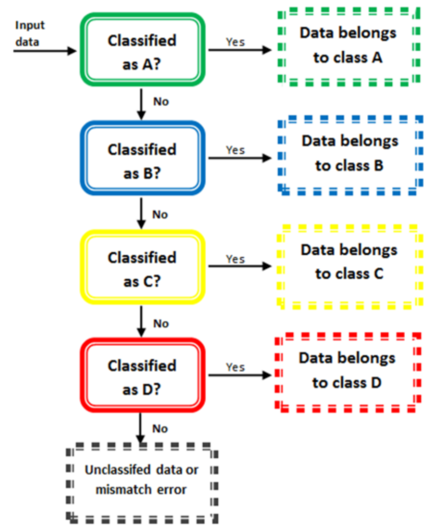

Fig. 3. A traditional hierarchical multiclass scheme. In this example, the decision priority is given from the top to the bottom ($\lambda_A>\lambda_B>\lambda_C>\lambda_D$). This scheme is similarly extended to the multisource approach.

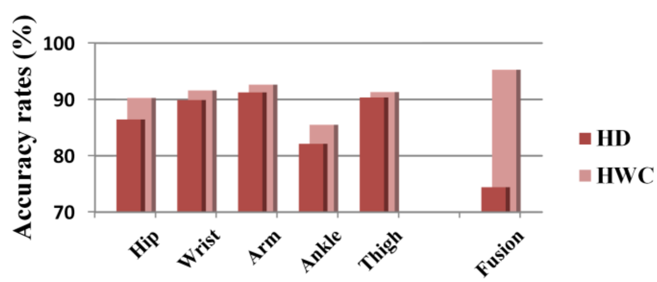

Fig. 4. Accuracy rates using HD and HWC schemas respectively. Results for each source classifier are identified with the corresponding sensor label. Fusion is referred to the combined use of the different source classifiers.

TABLE I

THREE BEST FEATURES SELECTED BY EACH FEATURE SELECTION SCHEMA USED. THE FEATURES ARE USED FOR THE CORRESPONDING CLASS CLASSIFIER DEFINED THROUGH THE ACCELEROMETER AND ACTIVITY OF SPECIALIZATION.

	Hip	*Wrist*	*Arm*	*Ankle*	*Thigh*
Walking	Y axis ar5 burg-thd & Y axis ar5 fb-thd & Y axis ar5 gl-thd	Y axis ar3 yw-harmonic mean & X axis ar3 ls-harmonic mean & X axis ar3 burg-harmonic mean	Y axis arma3 coef a-max & Y axis arma3 coef a-geometric mean & Y axis arma3 coef a-5th moment	Y axis hilbert imag-trimmed mean & Y axis hilbert phase-kurtosis & Y axis hilbert phase-fisher asymmetry coef	X axis arma3 coef a-fisher asymmetry coef & X axis arma3 coef c-fisher asymmetry coef & X axis ar2 burg-max
Sitting and relaxing	X axis arma4 coef a-arithmetic mean & X axis arma4 coef a-trimmed mean & X axis arma4 coef c-arithmetic mean	Y axis amplitude-4th moment & Y axis amplitude-range & Y axis hilbert real-4th moment	X axis ar2 yw-max & X axis ar2 burg-max & X axis ar2 fb-max	X axis ar3 burg-harmonic mean & X axis ar3 burg-geometric mean & X axis ar3 burg-median	X axis amplitude-std & X axis amplitude-max & X axis amplitude-min
Standing still	X axis hist-fisher asymmetry coef & X axis hist-kurtosis & X axis hist-max	X axis arma4 coef a-median & X axis arma4 coef a-min & X axis arma4 coef a-moda	Y axis amplitude-min & Y axis amplitude-moda & Y axis amplitude-5th moment	Y axis hist-kurtosis & X axis wavelet d3-zero crossing counts & Y axis hist-fisher asymmetry coef	Y axis hist-fisher asymmetry coef & Y axis hist-5th moment & Y axis hist-4th moment
Running	X axis amplitude-std & X axis amplitude-energy & X axis amplitude-max	X axis amplitude-std & X axis amplitude-energy & X axis amplitude-max	X axis amplitude-std & X axis amplitude-energy & X axis amplitude-geometric mean	X axis amplitude-kurtosis & X axis amplitude-std & X axis amplitude-geometric mean	X axis amplitude-std & X axis amplitude-geometric mean & X axis amplitude-4th moment
Bicycling	X axis ar2 burg-max & X axis ar3 burg-thd & X axis ar2 fb-max	X axis wavelet d2-zero crossing counts & Y axis wavelet a2-zero crossing counts & Y axis wavelet d2-zero crossing counts	Y axis ar3 burg-fisher asymmetry coef & Y axis ar3 fb-fisher asymmetry coef & Y axis ar3 gl-fisher asymmetry coef	Y axis wavelet a4-zero crossing counts & Y axis arma3 coef a-max & Y axis arma3 coef c-max	Y axis ar2 burg-energy & Y axis ar2 burg-min & Y axis ar2 burg-moda
Lying down	X axis arma2 coef a-max & X axis arma2 coef c-max & X axis arma2 coef a-harmonic mean	Y axis arma3 coef a-thd & Y axis arma3 coef c-thd & Y axis wavelet d4-kurtosis	X axis hilbert mod-median & X axis hilbert mod-harmonic mean & X axis hilbert imag-kurtosis	X axis min phase reconstruction-fisher asymmetry coef & X axis min phase reconstruction-min & X axis min phase reconstruction-moda	X axis arma2 coef a-harmonic mean & X axis arma2 coef c-harmonic mean & X axis arma4 coef a-fisher asymmetry coef
Brushing teeth	X axis ar6 fb-median & Y axis ar3 ls-fisher asymmetry coef & X axis ar6 burg-median	X axis arma4 coef a-kurtosis & X axis arma4 coef c-kurtosis & X axis ar4 ls-harmonic mean	Y axis wavelet a4-zero crossing counts & Y axis wavelet d1-max & X axis ar6 burg-kurtosis	Y axis ar6 burg-median & Y axis ar6 gl-median & Y axis ar6 ls-median	Y axis hilbert imag-kurtosis & Y axis amplitude-kurtosis & Y axis hilbert real-kurtosis
Climbing stairs	Y axis ar6 burg-arithmetic mean & Y axis ar6 burg-trimmed mean & Y axis ar6 fb-arithmetic mean	X axis wavelet a3-trimmed mean & X-Y axis cross correlation function-zero crossing counts & X axis autocorr function-zero crossing counts	Y axis ar3 burg-min & Y axis ar3 burg-moda & Y axis ar3 fb-min	X axis wavelet d2-zero crossing counts & X axis wavelet d1-zero crossing counts & Y axis hist-pos. of max	Y axis energy spectral density-entropy & X axis hist-pos. of max & Y axis hist-pos. of max

decision (HD, see Fig. 3) and our approach (HWC) are respectively tested. Considering the potential of binary decision trees (DT), they have been considered to form the binary or class classifiers, using the three best features selected by using the cited ROC model (Table I). The results are shown in Fig. 4.

If we compare the results obtained for each model, it is clear that the HWC improves significantly the performance of the HD solution. This is quite remarkable for the fusion approach, with an improvement of more than 20%. About that, we want to stress on the importance of the use of the weights in a proper way. The weights employed for the HD approach are the same for the HWC. In fact, the main difference is how these parameters are taken into account to obtain the final decision. In the HD approach when a classifier is wrong the decision offered for the rest of less significant classifiers is not considered, so the particular error is spread to the rest. Conversely, the HWC takes into consideration all the decisions so the particular errors are softened in overall.

As was mentioned in section 3, if source classifiers offer outstanding accuracy results, fusion approach may be omitted. This can be seen in Fig.4 for some source classifiers as based on the *arm* or the *wrist* accelerometer which define suitable recognition systems (~92%), so for this problem it would be enough to use one of these sensors, something especially important in wearable monitoring contexts. In any case, the fusion approach allow us to obtain a more robust and efficient solution.

V. CONCLUSION

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 use of a hierarchical weighted classification scheme offers several advantages to traditional hierarchical priority models. It is clear that using the same weighting parameters, the use of a combined linear model is preferable to the traditional priority based scheme. In addition, no more computational requirements are needed to accomplish the recognition task.

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 related problems or others (*UCI repository* [4]) with a spread range of classes.

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