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Physical activity recognition from sub-bandage sensors using both feature selection and extraction

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Abstract. In this paper, we present a neural network-based approach to classify the activities performed by 40 subjects by analyzing sub-bandage pressure signals. The approach includes an input dimensionality reduction obtained employing both feature extraction and feature selection techniques. The results show that our model is able to classify the activities performed with 98.12% accuracy.

1 Introduction

Recently, there has been a considerable research effort directed toward Human Activity Recognition (HAR) by means of wearable devices (e.g., smartphones, accelerometers, GPS sensors, physiological sensors). The identification of human body positions or activities has become of growing interest in many fields, e.g., medical, security, entertainment, tactical, military [1]. Possible applications are i) the recognition of falls of elderly people, ii) the monitoring of the rehabilitation of patients during the therapy, to detect abnormal activities or verify the correctness of exercise therapy, iii) the support of decision making processes in tactical or military contexts, etc. Physical activities include *static* postures, such as sitting, standing, laying, etc., and *dynamic* activities, such as walking, running, stairs climbing, etc. It is obvious that static postures are typically easy to distinguish from dynamic activities, while the discrimination between two dynamic activities, or two static postures, e.g., sitting and standing, may be not trivial.

In this paper we deal with activity recognition of dermatologic patients with venous ulcers during rehabilitation. In dermatology, venous ulcers are very frequent lesions of the skin of the legs, due to compromised functioning of the blood

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circulation. To repair these ulcers, the blood circulation must be enhanced by exploiting the calf muscle pump which allows the blood to be moved back to the heart. The first-line therapy to re-establish the blood circulation is the compression therapy [2][3]. In this therapy, a compression bandage is applied on the leg of the patient thus providing a pressure, which is high at the ankle and gradually reduces towards the knee. The pressure applied by the bandage allows to repair the ulcer, typically, in a few months. The pressure applied by the bandage, and thus the efficacy of the therapy, depends on several factors: i) the type of bandage (depending, e.g., on the elasticity); ii) the correct application of the bandage: an appropriate pressure should be applied in several parts of the leg according to the position of the ulcer, and the pressure should remain constant as much as possible between bandage applications; iii) the activities performed by the patient during the therapy (e.g., walking, standing, etc.). In fact, the sub-bandage pressure may vary significantly during the physical movement of the patient, thus affecting the healing rate [4]. Therefore, the possibility to track and analyze the movements made by the patient during the treatment, along with the sub-bandage pressure values, has become of the utmost importance in order to, e.g., i) understand the reason why a given treatment is working or not, or a therapy is better than another, ii) determine if the sub-bandage pressure assumes correct values during patient's movements. Despite this, in current clinical practice, sub-bandage pressure is not monitored to track the efficacy of the treatment [5][6], and existing clinical data do not take into account the effects of leg movements on sub-bandage pressure during treatment [5]. Moreover, it is unlikely that patients write down reports of their daily physical activity [7]. On the other hand, the research in wearable sensors has spread in recent years making available small non-intrusive sensors to detect physical movements by means of accelerometers or other clinical parameters, e.g., the sub-bandage pressure, heart rate, electrocardiogram (ECG) signal [8][9]. Among the techniques adopted, machine learning has been deeply employed to classify the activities by means of user's smartphone movements, represented by acceleration signals. In [10], a neural network (NN) is employed to recognize ambulatory activities from acceleration signals with an overall accuracy of 95%. In [11], the authors employ a Support Vector Machine (SVM) to discriminate between four activities with an accuracy of 92.25%, by using as features the coefficients of the autoregressive model built on the time-series data. In [12], the authors detect, with an accuracy of 97.9%, the activity performed, by using NNs, autoregressive models, and linear-discriminant analysis. In [13], the authors employ the ECG signal to distinguish among four activities with an accuracy of 95%, by using a neuro-fuzzy classifier.

A further problem in biomedical signal analysis is the high-dimensionality of data, which typically requires a preliminary step of input dimension reduction to highlight significant information contained within the signal, and discard noisy information. The dimension reduction can be obtained by means of feature selection (FS), feature extraction (FE), or both. More in detail, the significant variables chosen can be values directly obtained from the signal (FS). Alternatively, when it is not possible or not convenient to take into account the signal as a whole, the signal is summarized by extracting representing variables (FE). A well-known method for FS is *forward*

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feature selection (FFS). It begins by evaluating all feature subsets consisting of one feature, according to a certain *criterion function*, i.e. a model approximating the relationship between inputs and outputs. Then, it finds the best subset containing two features (the one previously selected and one from the remaining features), three features, and so on. The final subset is the best one among all the subsets generated.

The aim of this work is to classify the type of activity performed by a patient, by analyzing how the sub-bandage pressure varies, in order to check if the patient has followed the clinical instructions, and to evaluate the efficacy of the bandage in relation to the activity performed. The objective is to provide healthcare professionals with a fast and efficient analysis tool for effective treatment plans.

2 Data

The data were collected during a clinical experimentation involving 40 (healthy) homogeneous subjects and a measurement device. The subjects are considered homogeneous in terms of height, ranging from 162 to 182 cm, circumference of the calf, ranging from 34 to 41 cm, and circumference of the ankle, ranging from 20 to 23 cm. The device consists of 3 independent force-sensing resistor sensors (Interlink Electronics FSR® 402). A compression bandage was applied on the leg of each subject, and the sensors were applied under the bandage in three different positions (calf, insertion of the gastrocnemius muscle, supramalleolar region) to measure sub-bandage pressure (expressed as electrical resistance (Ohm)) during different activities. Each subject wears the bandage for a time interval of about 3 minutes with a sampling time of about 82 ms. During this time interval each subject performs four different activities for the same amount of time. Measurements were collected while subjects perform the following cycle of activities: i) *supine posture*, ii) *walking*, iii) *dorsiflexion standing*, and iv) *stairs climbing*. The data from the three sensors were preprocessed in order to remove some noise (a few seconds) at the beginning and at the end of the subject's experimentation, due to the repositioning of the device, and during the changes of activity. After this preprocessing, the length of the time interval associated with each activity or posture results to be about 37 seconds. Thus, the post-processed dataset consists of 160 samples belonging to 4 possible classes. Each sample is represented in terms of three signals of time length of about 37 seconds, with each signal corresponding to 457 data points.

3 Proposed Methodology

The aim of this paper is to recognize the activity performed starting from the signal representation in the time domain, coping also with a high-dimensional input context. The model used is a multi-layer perceptron (MLP) for classification. The inputs to the NN are derived by first *extracting,* and then *selecting*, appropriate statistical parameters from the available signals, in order to reduce the dimensionality of the problem, and maintaining high accuracy. The methodology consists of three steps: 1) FE, 2) FS, and 3) leave-one-out (LOO) classification, all described in the following.

3.1 Feature extraction

The FE step allows us to appropriately summarize the signals. We took into account the three sensors as separate signals, in order to fully exploit the information in the data. In fact, e.g., we may find that one sensor is best tailored to recognize a given activity, while may be less useful to recognize the other activities. We considered a set of 13 different well-known and widely-used features extracted from each signal. As each sample consists of three signals (corresponding to three different sensors), we extracted the 13 features from each sensor's signal, obtaining a total of 39 different features. In Table 1 we list the features extracted, along with their expressions.

3.2 Feature selection

After FE, the number of features, i.e., 39, is still too high to develop a low-complexity model, thus we perform FS by means of FFS. The criterion function is the error made by an MLP having as inputs, at each step, the selected features, and as outputs the class label, i.e., the corresponding activity, represented as a binary vector of 4 elements. We stopped the FFS process when the error did not decrease any more. With the aim of having all the inputs represented within the same scale, the input features are normalized in [0, 1] according to the max-min formula. We repeated the FFS process 10 times by randomly extracting from the data, respectively, 80%, 10%, and 10% for training, test, and validation sets. We employed the *early stopping* method to avoid overfitting during the training of the network. Then, we considered the best most frequently selected features, namely, *Mi* from the first sensor, *E*, *S*, *HjM*, *RMS*, and *Mi* from the second sensor, and *WA* from the third sensor.

3.3 Leave-one-out classification

Now that each sample is described in terms of a reduced number of features, an MLP for classification can be developed. The MLP has 7 inputs, and 4 outputs. To fully exploit the data, and in order to obtain fair classification results, we performed a sort of LOO cross-validation (CV) procedure (LOO-CV). LOO-CV works as follows. Given D data observations, the model is trained with D-1 observations and then is tested on the observation that was left out. The process is repeated D times until every observation is used once to evaluate the out-of-sample performance. In our case, we perform the LOO-CV considering the subjects, i.e., *sets* of observations instead of single observations. More in detail, we tested the model on the four observations, corresponding to the four activities performed by a given subject, after training it on the observations related to the other 39 subjects. Thus LOO-CV corresponds to the repetition of 40 training and test processes. Each process was repeated 10 times and the best performing NN was selected. The LOO-CV performance of the model is computed as the mean performance over the 40 trials. Table 2 shows the obtained LOO-CV results in terms of the following measures [14]: accuracy, precision, recall, and F-measure, by class, i.e., activity, and averaged over all classes. The model was developed in the Matlab® environment. We used the Matlab®'s default values for the parameters of the MLPs employed in the experiments, namely, 10 neurons in the

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hidden layer, and hyperbolic tangent sigmoid function as transfer function both for the hidden and the output neurons.

Finally, we compared our results with those obtained employing a different FS method, and a different classifier (an SVM), by showing the superiority of our results. More in detail, the FS step was performed by individually evaluating the 39 features, and by selecting the set of p highest ranked features (with p ranging from 1 to 10). The best set contains p = 8 features, i.e., *HjM*, *HjC*, and *V* from the first sensor, *WA*, *E*, *Ma, SSC* and *K* from the second sensor. Then, we repeated the LOO-CV as explained previously using a multi-class SVM classifier, consisting of 4 one-against-all standard SVM classifiers. The multi-class SVM classifier, fed with the 8 features, obtained average values for precision, accuracy, recall, and F-measure of 81.8%, 81.8%, 82.5%, and 81.9%, respectively.

Feature	Expression
Root Mean Square (RMS)	$RMS(X) = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} {x_i}^2}$
Mean Absolute Deviation (MAD)	$MAD(X) = \frac{1}{N} \cdot \sum_{i=1}^{N} \lvert x_i - \mu \rvert$
Entropy (E)	$E(X) = -\sum_{i=1}^{N} p_i \cdot \log_2 p_i$
Maximum (Ma)	$Ma(X) = x_i{:}\, x_i > x_j\ \forall j \neq i, i = 1, \dots N, j = 1, \dots N$
Minimum (Mi)	$Mi(X) = x_i{:}\, x_i < x_j\ \forall j \neq i, i = 1, \dots N, j = 1, \dots N$
Variance (V)	$V(X) = \frac{1}{N} \cdot \sum_{i=1}^{N} (x_i - \mu)^2$
Hjorth Mobility (HjM)	$HjM(X) = \sqrt{\frac{V(X')}{V(X)}}$
Hjorth Complexity (HjC)	$HjC(X) = \frac{HjM(X')}{HjM(X)}$
Slope Sign Change (SSC)	$SSC(X) = \sum_{i=2}^{N-1} f[(x_i - x_{i-1}) \cdot (x_i - x_{i+1})]\ , f(s) = \begin{cases} 1, & if\ s > \vartheta_1 \\ 0, & otherwise \end{cases}$
Willison Amplitude (WA)	$WA(X) = \sum_{i=1}^{N-1} f(\lvert x_{i+1} - x_i \rvert)\ , f(s) = \begin{cases} 1, & if\ s > \vartheta_2 \\ 0, & otherwise \end{cases}$
Kurtosis (K)	$K(X) = \frac{\sum_{i=1}^{N} (x_i - \mu)^4}{N \cdot \sigma^4}$
Skewness(S)	$S(X) = \frac{\sum_{i=1}^{N} (x_i - \mu)^3}{N \cdot \sigma^3}$
Cumulative Length (CL)	$CL(X) = \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$

Table 1: Features extracted. We indicate with X the signal, with x_i a data point of X, and with N the number of data points of X. Further, μ, X' , and σ are, respectively, the arithmetic mean, the first derivative, and the standard deviation of the signal X, p_i is the probability of x_i. We set the values of the thresholds ϑ_1 and ϑ_2 to 0.1, based on a trial-and-error approach.

Activity	Precision	Accuracy	Recall	F-measure
Supine posture	97.5%	97.5%	100%	98.73%
Walking	97.5%	97.5%	97.5%	97.5%
Dorsiflexion standing	100%	100%	97.56%	98.76%
Stairs climbing	97.5%	97.5%	97.5%	97.5%
Average	98.12%	98.12%	98.12%	98.12%

Table 2: Classification results.

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4 Conclusions

We have presented an approach able to discriminate among four different human physical activities, by using sub-bandage pressure signals collected from 40 subjects. To reduce the input dimensionality, we used both FE and FS, and we obtained an average accuracy of 98.12%. As future work we aim to exploit other sensor fusion techniques in order to improve the results by fusing the information coming from the different sensors.

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