USER VERIFICATION FROM WALKING ACTIVITY
First Steps towards a Personal Verification System

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Abstract: In this work, first encouraging results in user verification by walking activity using a wearable device are reported. A discriminative machine learning pipeline is proposed for user verification. A general walking classifier based on AdaBoost is used for personalization adding data related to the verified users. An ensemble of One-Class classifiers is created for user verification. This novel technique proves to achieve very high performances from both classification accuracy and computational cost point of view. Results obtained shows that users can be verified with high confidence, with very high value of performance metrics.

1 INTRODUCTION

Privacy in today's digital society is one of the most important and controversial topics. Consider, for instance, that your smart-phone, containing all kind of personal informations, is stolen. If the system was able to verify its owner while it is being carried, it could automatically block or send an alert message in case of detecting a non verified user. In this context, the verification of authorized users using walking activity patterns is of great interest related to security and privacy.

Recognizing physical activities like walking is an emerging field of research. Recognizing all type of everyday life activities might be in the short future a fundamental application in pervasive computing. Even if first works about activity recognition used audio and video streams (Clarkson and Pentland, 1999), in many recent works activity recognition is based on classifying sensory data using one or many accelerometers. Accelerometers have been widely accepted due to their miniaturization, their low-power requirements and for their capacity to provide data directly related to motion. Modern smart-phones as i-Phones or Android-based phones have an integrated tri-axial accelerometer sensor.

In (Mannini and Sabatini, 2010), authors give a complete review about the state of the art of activity classification using data from one or more accelerometers. In their review, seven basic activities and transitions between activities are classified from five biaxial accelerometer placed in different parts of the body, using an high dimensional features vector and a Hidden Markov Model classifiers, achieving 98.4% of accuracy. In (Lester et al., 2006), authors summarize their experience in developing an automatic physical activities recognition system. In their work, the location of the sensor has very small impact on their results. Additionally, the performance of the system improves as data from different users is used and they achieve the best result fusing information from accelerometers and microphones.

Although much effort has been put in activity recognition, user verification by mean of accelerometer data has been rarely addressed. The closest work to user verification concerns user identification. There is a fundamental difference between identification systems and verification ones. While in identification systems one tries to discriminate among different users, in verification the purpose is to check that data belong to the authorized user of the system without prior knowledge of data of the intruders. Note that, if one tries to mimic the behavior of the verification system using identification, one must model all possible non-authorized users – which is unfeasible in general settings. In (Mäntyjärvi et al., 2005), user identification have been performed using correlation, frequency domain and data distribution statistics, ensuring an error rate of 7%. In (Gafurov et al., 2006), a biometric user authentication system based on a person gait is proposed. Applying histogram

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similarity and statistics about walking cycle, authors ensure 5% of identification error rate. Recently, some efforts in user verification have been done also in (Derawi et al., 2010), where, using the accelerometer of an Android-based mobile phone, walking data have been collected from 51 testers walking in an interior corridor. From the best of our knowledge, that work represents the first one using data collected using a real mobile phone.

In our work, first encouraging results in **user verification** by walking activity are reported. In our lab, a wearable system easy to use and comfortable to bring has been developed. Motion, audio and photometric data of five basic every-day life activities have been collected from ten volunteer testers. The activities performed are walking, climbing up/down stairs, staying standing, talking with people and working at computer. Testers performed activities where they want and for the time they want. Developing a custom wearable system allows simulating the use of wearable devices people use everyday, such as mobile phones, but with the complete freedom to customize each software level, from the operating system to the application level. We propose a discriminative machine learning pipeline for user verification. Discriminant classifiers have proven to be extremely efficient and powerful tools, even surpassing the performances of generative machine learning techniques. Using this framework, a two stage process is defined. In the first stage, a general walking classifier is trained using a baseline training set using en ensemble strategy based on AdaBoost (Freund and Schapire, 1999). The classifier is subsequently personalized adding data of verified users in order to boost the performances of the walking activity for those users. Since AdaBoost is an incremental classifier, this process is extremely efficient since it just needs to add further weak classifiers to the original baseline classifier. Once the walking activity is detected for the specific user, we must verify if it is an authorized user. From the discriminative point of view, user modeling without counter examples can be done using One-Class classification strategy (Tax, 2001). In One-Class classification, the boundary of a given dataset is found and the confidence that data belong to that set depends on the distance to the boundary. Thus, in the second stage, a One-Class ensemble is created using as base classifier a convex-hull on a reduced feature space. In this work, we shown that this novel technique performs well from both classification accuracy and computational cost point of view. Results obtained prove that users can be verified with high confidence, with very low false positive and false negative rates. The layout of this paper is as follows. In the next section, we describe the wearable device developed and the data acquisition process. In Section 3, we describe the features extraction process and in Section 4, the classifiers used for the classifications. In Section 5 we show results obtained and finally, in Section 6, we discuss results and conclude.

2 THE WEARABLE DEVICE

In this section, the wearable device and the data acquisition process are described. The wearable system, called BeaStreamer, is built around the Beagle Board (TI, 2008). The device has small form factor and it is comfortable to wear. Using BeaStreamer, data have been collected from ten testers performing five activities.

2.1 BeaStreamer

BeaStreamer is a wearable system designed for multi-sensors data acquisition and processing. The system acquires audio, video and motion data. The system can be easily worn in one hand or in a little bag around the waist. The audio and video data flows are acquired using a standard low-cost web cam. Motion data are acquired using a Bluetooth tri-axial accelerometer. The core of the system is the Beagle Board, a low-power, low-cost single-board computer built around the OMAP3530 system-on-chip. OMAP3530 includes an ARM Cortex-A8 CPU at 600 MHz, a TMS320C64x+ DSP for accelerated video and audio codecs, and an Imagination Technologies PowerVR SGX530 GPU to provide accelerated 2D and 3D rendering that supports OpenGL ES 2.0. DC supply must be a regulated 5 Volts. The board uses 2 Watts of power. An AKAI external USB battery at 1700mAh allows approximately 3 hours of autonomy for the system in complete functionality. A Linux Embedded operating system has been compiled adhoc for the system and standard software interfaces such as Video4Linux2 and BlueZ can be used for data acquisition. It is possible to connect directly a monitor and a keyboard to the board, using the board as a standard personal computer. It is also possible enter into the system by a serial terminal. The GStreamer framework has been used for acquiring audio video and Bluetooth motion data allowing to easily manage synchronization issue in the data acquisition process. The board can be programmed in C or Python.

2.2 Data Acquisition

The system works with video, audio and accelerometer data. It takes photos, grabs audio and receives data from the accelerometer via Bluetooth. Accelerometer data are sampled at 52Hz with a resolution of $\pm 4g$. All sensors are localized on the chest. Data have been collected from ten volunteers, three women and seven men with age between 27 and 35. Testers were free to perform activities in the environment they selected overpassing the laboratory setting limitation. All the activities have been performed for at least 15 minutes. Activities performed are climbing up/down stair,walking,talking with people,standing and working at computer. For labeling activities, only the sequential order of the activities has been annotated. Every time an activity is performed, testers have to start the system that after booting, automatically starts the acquisition task while the user is already performing the activity. Even if audio and video have been also acquired, in this work only accelerometer data are taken into account.

3 FEATURES EXTRACTION

Tri-axial accelerometers produce three acceleration time series, one for each motion axis. Before extracting features, a smoothing filter has been applied to the signal. Each acceleration time series has been windowed using a 2 seconds window. Mean value, standard deviation, skewness, kurtosis, mean value of the number of samples where the normalized waveform is positive, difference between the maximum value and the minimum value in a normalized waveform and number of zero-crossing of the normalized waveform have been computed as features. Once features from 1 to 4 are computed, the acceleration data is normalized and features from 5 to 7 computed. In Figure 1, six seconds of acceleration related to walking activity on Z axis are reported and features extracted from the waveform are drawn. Feature 5 is denoted as *width*, Feature 6 as *height* and Feature 7 as *zero-crossing*. Finally, a 22-dimensional feature space is obtained.

4 THE VERIFICATION PIPELINE

A two-stage pipeline is proposed for user verification. The overall user verification system is shown in Figure 2. The general walking activity classifier, based on AdaBoost, is trained using many walking activities from many persons. It receives as input the features extracted from accelerometer data and it detects

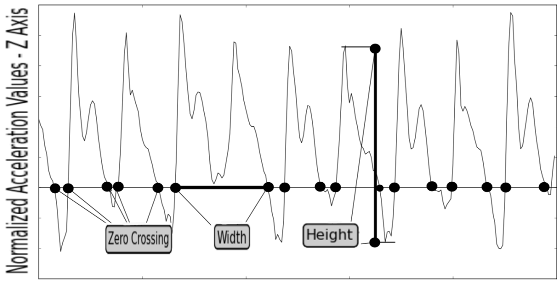

Figure 1: Graphical description of Feature 5 (width), Feature 6 (height) and Feature 7(zero-crossing) extracted from Motion Data.

when walking activities occur. The general classifier is subsequently personalized adding data of the specific users. Using a further training step, the performances of the walking activity are considerably enhanced for the specific user. In this way, the personalized walking activity classifier is able to filter non walking activities and a big load of walking activities from other users. The incremental training process becomes extremely simple and efficient since AdaBoost just needs to add more weak classifiers to the original baseline classifier. When a walking activity is detected, the verification task is provided by the user verification ensemble. This classifier receives as input the features computed on the accelerometer data and checks if the walking activity belongs to the verified user or not. User verification is performed by an ensemble of naive One-Class classifiers using a convex hull to define the region characteristic of the specific user in a reduced features space.

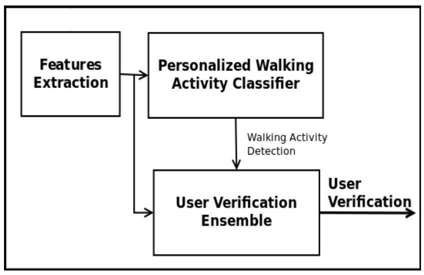

Figure 2: Block Diagram of the User Verification System.

4.1 Walking Classification

AdaBoost (Freund and Schapire, 1999) is an efficient algorithm for supervised learning. AdaBoost boosts the classification performance of a weak learner, by combining a collection of weak classification functions to form a stronger classifier. The algorithm combines iteratively the weak classifiers by taking into account a weight distribution on the training samples such that more weight is attributed to samples misclassified by previous iterations. The final strong classifier is a weighted combination of weak classifiers followed by a threshold. Table 1 shows the pseudocode for AdaBoost. The algorithm takes as input a training set $(x_1, y_1), \ldots, (x_m, ym)$ where x_k is a N-dimensional features vector, and y_k are the class labels. After T rounds of training, T weak classifiers h_t and ensemble weights α_t are used to assemble the final strong classifiers. AdaBoost training algorithm

Table 1: AdaBoost Algorithm.

- Given a training set $(x_1, y_1), \ldots, (x_m, y_m)$, with $x_k \in R^N$, $y_k \in Y = \{1, +1\}$;
- Initialize weights $D_1(k) = 1/m, k = 1, \ldots, m$;
- For $t = 1, \ldots, T$:

1. Train weak learner using distribution D_t
2. Get weak hypothesis $h_t : X \to \{-1, +1\}$ with error $\varepsilon_t = Pr_{k \sim D_t}[h_t(x_k) \neq y_k]$
3. Choose $\alpha_t = \frac{1}{2} \ln(\frac{1-\varepsilon_t}{\varepsilon_t})$
4. Update :
$$D_{t+1}(k) = \frac{D_t(k) \exp(-\alpha_t y_k h_t(x_k))}{Z_t}$$
where Z_t is a normalization factor chosen so that D_{t+1} will be a distribution.

- Output the final hypothesis
$$H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x))$$

is incremental. After n training steps on a dataset, it is possible to add further m training steps using another dataset by adding new weak classifiers. This characteristic is crucial in the personalization step of the proposed pipeline. For classifying walking activity, AdaBoost is trained only using features from 5 to 7. As second step, the classifier has been further trained using all the features related to the specific subject, for each subject. The weak classifiers used are decision stumps.

4.2 User Verification

Based on the intuition derived from visual feature analysis, a One-Class classifier ensemble has been trained using the convex hull generated on a reduced features space. The underlying idea is shown in Figure 3. Data related to each user are localized in a specific region of the features space. Training the One-Class classifier means building the convex hull and defining the region of the space where user data lies. When a new point appears, if the point is inside the convex hull, then it represents a walking activity of the user. If the point does not belong to the interior of the convex hull, it has a confidence value to belong to the user that is inversely proportional to the distance from the border of the convex hull. Using the convex hull is theoretically justified in (Bennett and Bredensteiner, 2000). The authors state that finding the maximum margin between two sets is equivalent to finding the closest points in the convex hull. Therefore, modelling the convex hull around features points is equivalent to use an SVM classifier if classes do not overlap. The computational complexity for building the convex hull is $O(n \ log \ n)$ as reported in (Toussaint, 1985), only using $m \ll n$ points stored in memory, with n being the number of training points. For those reasons, such algorithm can easily run in devices with limited computational and memory resources. The

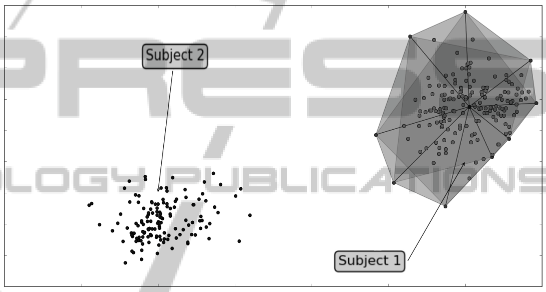

Figure 3: User verification using a convex hull as One-Class classifier.

One-Class classifier has been trained for each pairwise combination of features, obtaining in this way an ensemble of One-Class classifiers. The final result is obtained averaging the results of every single One-Class classifier. The algorithm for the convex hull One-Class classifier is reported in Table 2.

5 EXPERIMENTAL RESULTS

In order to validate walking activity classification accuracy and user verification performances, cross-validation has been used. Cross-validation is a technique for assessing how the results of a classification process generalize on an independent data set. A round of cross-validation is performed partitioning the entire dataset into different subsets, performing training on one set and testing the classifier on an other dataset. There exist many different cross-validation schemes. In this setting, a Leave-One-User-Out (LOUO) cross validation scheme has been used. LOUO cross-validation involves using a single user for testing purposes and the remaining users as training data. This is repeated such that each user in the dataset is used once as testing data. In the fol-

Table 2: Ensemble One-Class Algorithm.

Train:
-Given a training set $X[m,n]$, with $X \in R^{M \times N}$;
1. For $i = 0 : N$
2. For $j = i+1 : N-1$
3. Compute the convex hull $Ch\{i, j\}$ for the dataset $X_{new} = \{X[i,n], X[j,n]\}$

Return Ch

Classify:
- Given a dataset $D[m,n]$, with $D \in R^{M \times N}$;
- Initialize Res[i,j]=0
1. For $i = 0 : N$
2. For $j = i+1 : N-1$
3. If $(D[i], D[j])$ is inside $Ch[i, j]$
4. $Res[i, j] = 1$
5. Else
6. $Res[i, j] = e^{-dx}$ where d = distance from the border

-Return the mean of all results for each point

lowing subsections, all the results relative to general walking classification, personalized walking classification and user verification are reported.

5.1 General Walking Classification Results

The first step of the system aims at distinguishing the walking activity disregarding the user information. This value is used as reference value for further improvements by means of personalization. Classification performances on general walking classification have been evaluated using LOUO scheme with AdaBoost with 50 Decision Stumps trained only using features from 5 to 7 – features that do not depend on the specific user. Overall classification performances obtained are reported in Table 3.

Table 3: Classification Performances for General Walking Classifier.

Precision	**Recall**	**Specificity**	**Sensitivity**
95.4%	95.5%	98.4%	98.5%

5.2 Personalized Walking Classification Results

The results obtained from the classifier are good but further improvement can be achieved if the training set has access to actual authorized user data. Since these data must be acquired compulsory for the verification process, they can be used to increase the performances of step 1. In this step, the classification performances for a walking activity for every single subject have been evaluated. Datasets have been separated for the user and the rest of persons. For evaluating the performance taking into account data from the authorized user a five-fold cross validation process is performed for each fold of LOUO cross-validation. This means that the classifier has been trained on 80% of the data of all the persons and on 80% of the data for the specific subject. The resulting classifier has been tested on the remaining 20% of the data of both the rest and the specific subject. This process is repeated 5 times for each user and results averaged. The classification performances are reported in Figure 4. Adding a further training to the classifier has the effect that might be expected. The classification performances for general walking classification decrease while the classification performances for the specific subject are considerably improved. The walking classifier works with very high performances only on walking data of the specific subject, heavily filtering the walking activities of other subjects. For the majority of the subjects, the classification accuracy for a walking activity is above 98%.

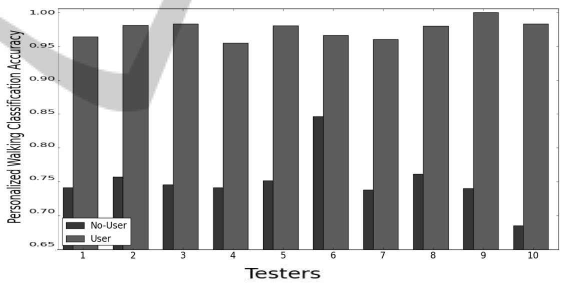

Figure 4: Personalized Walking Classification Accuracy.

5.3 User Verification Results

The verification process must ensure two things. First of all, the system must not block given an authorized user. This means that the false negatives value should be as small as possible. This is measured by the *Sensitivity* parameter, defined in Equation 1.

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (1)$$

On the other side, the system has to avoid as many intrusions as possible. This is measured by the number of false positives and reflected in the *Positive Predictive Value* parameter, defined in Equation 2.

$$PositivePredictiveValue = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

Both parameters are critical and measure the degree of goodness of the system. For verification purposes, a five-fold cross validation process is performed for each fold of LOUO cross-validation. Again, an Ensemble One-Class classifier has been trained on the 80% of the data of the authorized user and tested on the remaining 20% of that user and on all data from the rest of the subjects. This process is repeated five times for each user using five different, non overlapping data subsets for testing. The verification accuracy obtained is reported in Table 4. Both sensitivity

Table 4: Performances of the Verification System.

User	Sensitivity	PPV	User	Sensitivity	PPV
Subj 1	0.922	0.981	Subj 6	0.914	0.991
Subj 2	0.976	0.718	Subj 7	0.835	0.931
Subj 3	0.97	1.	Subj 8	0.91	0.972
Subj 4	0.936	0.938	Subj 9	0.971	0.947
Subj 5	0.981	0.912	Subj 10	0.853	0.912

and positive predictive value are high. However, this value of sensitivity is not acceptable since we must minimize the system mistakes on authorized users. In order to improve this parameter, verification has been performed on subsequent temporal windows using an ensemble of Ensemble One-Class with a Majority Voting decision process. In Figure 5, it is shown how verification accuracy varies with respect to the size of the ensemble. Using bigger ensembles, equivalent to use wider temporal windows, improve significantly the accuracy for both parameters, ensuring very high sensitivity and positive predictive value. Starting from an ensemble of size 3, all the user sensitivities are above 98% and starting from an ensemble of size 5, all the positive predictive values are above 97%.

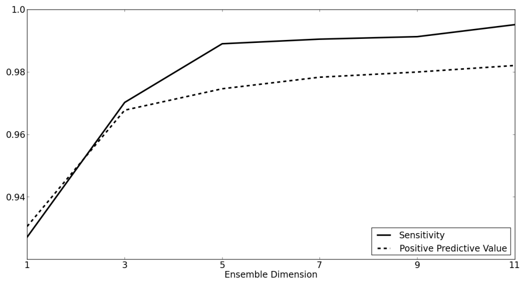

Figure 5: Sensitivity and PPV versus Ensemble Dimension.

6 DISCUSSION AND CONCLUSIONS

In this work, an User Verification System by walking activity using a discriminative machine learning pipeline has been proposed. Using a wearable system, motion data have been collected from 10 testers. Using motion data, classification of walking activity and user verification have been performed.

Results related to walking classification demonstrate that a walking activity can be separated from other activities and successfully classified. In particular, when the classifier is personalized for the specific subject, classification results are highly accurate and, for the specific user, the walking classifier reaches very high performances.

User verification has been performed with high accuracy. In particular, experiments show that results can be significantly improved when temporal information is taken into account in the verification process. Nevertheless, there exist still some subjects that can not be verified as desired. For instance, subject 10 and, in a special way, subject 7, have sensitivity lower respect to the others subjects. For subject 7, the worst case, verification accuracy obtained using an ensemble of 11 ensemble of One-Class classifiers is still much lower with respect to the other subjects. Due to the outliers, the convex hull has not well defined borders and the verification performances of these subjects are affected. More study must to be done on this subject.

From our point of view, using the convex hull as One-Class classifier has been a very practical way of tackling the problem of user verification ensuring very good results but more sophisticated techniques be suitable for this purpose. Using a One-Class SVM should characterize better the boundaries of users region, providing also robustness to outliers at the cost of increasing the processing time when specializing the system for an authorized user. Note that this process must be performed on the wearable system and training a One-Class SVM is computationally hard.

Finally, a more accurate validation of the system must be done using more testers and putting the sensor in different body locations. Putting the sensor on the chest is a realistic assumption, taking into account, for instance, that a mobile phone can be worn in the jacket pocket. However, for the development of a robust verification system, more locations need to be taken into account, such as pant pockets or even in the hands, providing more interesting and a challenging case of study.

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