Using Support Vector Machines for Atrial Fibrillation Screening

Daniel Rivera[1], César Veiga[1], Juan J. Rodríguez-Andina[2], José Fariña[2], Enrique García[3]
[1]Instituto de Investigación Sanitaria Galicia Sur (IISGS), Vigo, Spain
[2]Department of Electronic Technology, University of Vigo, Vigo, Spain
[3]Hospital Álvaro Cunqueiro, Vigo, Spain
Cesar.Veiga.Garcia@sergas.es, {jfarina, jjrdguez}@uvigo.es

***Abstract*—Atrial fibrillation is the most common type of arrhythmia in the world. Therefore, the development of suitable techniques for detection of atrial fibrillation is of paramount importance, particularly for ambulatory screening of potential patients. On the other hand, the current availability of wearable devices capable of monitoring biometric signals opens the door for such ambulatory screening to be affordably performed at a large scale. One of the main challenges in this context is the need for analyzing huge amounts of data. Computational intelligence techniques are good candidates to carry out this kind of analysis. This paper proposes the use of Support Vector Machines for heart rhythm analysis, aiming at discriminating between atrial fibrillation and sinus rhythm. Heart rate information is obtained from photoplethysmography sensors embedded in wearable devices. Experimental results obtained from real patients are presented and discussed, pointing to the suitability of the proposed solution for affordable atrial fibrillation screening.**

I. Introduction

Population aging is causing an increase in the demand for medical assistance in developed countries, in turn requiring an increase in medical expenses, which cannot be afforded in the long term in an economically sustainable way. One of the ways expense growth can be mitigated is by reducing the number of people requiring medical observation in hospitals, and another one is through early detection of diseases (which in most cases makes treatments not only cheaper but also easier and more effective). Portable [1] and wearable devices [2] can play a fundamental role in these two regards, by allowing ambulatory monitoring of potential patients (which has the additional advantage that patients are monitored during normal life, then allowing more realistic data to be obtained than if they are at rest in hospital).

Atrial fibrillation is the most common type of arrhythmia [3], the estimated numbers of persons with atrial fibrillation being over 33.7 million worldwide, with higher incidence and prevalence rates in developed countries [4]. It is one of the major causes of stroke, heart failure, sudden death, and cardiovascular morbidity in the world. Early diagnosis of atrial fibrillation is not an easy task, because it is usually a "silent" disease (with no "visible" symptoms). Approximately one third of patients develop "asymptomatic" atrial fibrillation, so they do not feel any sign of it. Early atrial fibrillation detection would allow patients to be protected by applying timely medical treatment. Smartphones [5]-[7] and wearable devices [8][9] can play a valuable role in this context, because they may allow the heart rate of potential patients to be monitored during relatively long periods of time with acceptable accuracy.

Photoplethysmography (PPG) sensors are typically available in wearable devices. PPG is a simple, low-cost optical technique that allows volume changes in blood vessels to be detected. Although changes in PPG signals are actually also due in part to breathing (among other low-frequency effects), it is possible to extract from them information about heart rate [10]-[12]. Two main problems currently limit the practical applicability of PPG sensors in wearable devices for ambulatory monitoring of potential atrial fibrillation patients. On one hand, noise caused by patients' movements during their normal, everyday life can significantly affect PPG signals. On the other hand, the amount of data to be processed is very high so, considering in addition the increasing number of people to be monitored, it is not practically feasible for medical staff to analyze them, like they do, for instance, with electrocardiograms. Automated means are necessary, at least to perform data analysis aimed at screening of patients. This, in turn, requires from the monitoring platforms significant processing power or high data storage capacity, both scarcely available in wearable devices. Computational intelligence techniques [13][14] are good candidates to carry out the required data analysis.

This paper addresses atrial fibrillation screening through the use of PPG signals and Support Vector Machines (SVMs) [15]. PPG signals are briefly introduced in Section II, where the way for extracting heart rate information from them is explained. Since the ultimate goal of this work is the development of a wearable-based ambulatory screening system, the wearable device currently being used to acquire PPG signals is also described in that section. Section III highlights the main characteristics of SVMs and discusses the data processing approach proposed for heart rhythm classification from heart rate information. Experimental results obtained from actual patients are presented and discussed in Section IV. Finally, the current conclusions of the work are summarized in Section V.

978-1-5090-1412-5/17/$31.00 ©2017 IEEE

II. Heart Rate Measurement from PPG Signals

A. PPG Signals and Heart Rate Measurement

PPG is an optical technique that allows volumetric measurements of internal human body organs to be obtained. It can be used for measuring oxygen saturation or blood pressure, as well as heart rate, as it can be realized by comparing electrocardiogram (ECG) and PPG signals. It can be noticed in Fig. 1 that peak-to-peak times are the same in both waveforms. Therefore, peak-to-peak times in noise-free PPG signals represent heart beat periods (the inverse of heart rate).

Fig. 1. Sample ECG (top) and PPG (bottom) signals (adapted from [10]).

PPG sensors are usually placed in ears, fingers, or toes. They use one or more light sources (e.g., LEDs) directed to the patient's skin and a photodetector (e.g., a photodiode) that measures, in some cases, the light reflected by tissues, bones, or blood vessels and, in other cases, the light that passes through those elements and exits the body.

Actual PPG waveforms consist of a "pulse" component, due to changes in blood vessel volume synchronized with heart beats, plus other components of lower frequency, due to volumetric changes caused by breathing, neurological activity, or body's own thermoregulation. In addition, measured PPG signals can be affected by several factors, e.g., patient's movements (Fig. 2) or tremors, which introduce artifacts in measured waveforms.

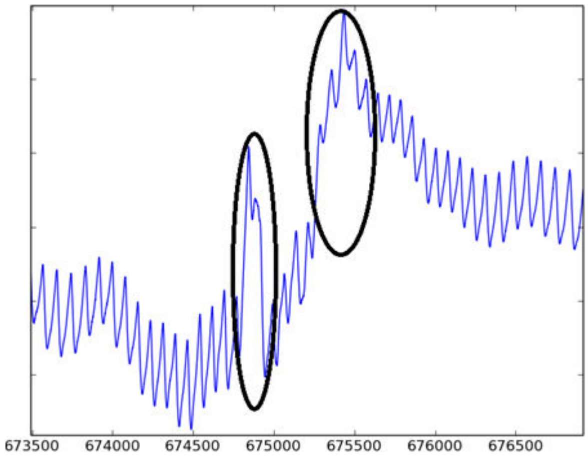

Fig. 2. Artifacts in PPG signal due to patient's movements.

The identification and separation of these artifacts are not trivial tasks, usually requiring signal processing techniques to be applied in order for reliable heart rate information to be obtained and then analyzed for accurate heart rhythm classification to be achieved. Artifact removal and separation of heart rate information from that corresponding to breathing and other effects are out of the scope of this paper (except for the brief description in Section II-B), and are addressed by the authors in other works. This paper focuses on the analysis of "clean" heart rate information for heart rhythm classification, obtained after suitable signal processing is applied to data provided by a PPG sensor. The computational intelligence-based approach proposed in this work for heart rhythm classification is described in Section III.

B. Data Acquisition and Cleaning

As stated in the previous section, PPG signals are usually measured in ears, fingers, or toes. However, for ambulatory monitoring of patients over long periods of time, it is much more convenient to place sensors in wristbands, as shown in Fig. 3.

Fig. 3. Wristband wearable device used in this work.

The wearable device used in this work is based on an AFE4403 Watch EVM [16], which includes not only a PPG sensor, but also a gyroscope and a processor, with which noise artifacts caused by patient's movement as well as signal components introduced by breathing and other effects can be removed. This is accomplished in two complementary ways:

1) First, during PPG data acquisition, samples are discarded if the gyroscope indicates significant patient's movement is taking place. Since the frequency range associated to noise caused by patient's movement has a significant overlap with that associated to heart rate, movement-related artifacts cannot be directly eliminated from the measured PPG signal, but this indirect method has to be applied instead.
2) Later, after applying time domain smoothing to the remaining PPG samples to extract heart rate information from them, if calculated values (in beats per minute) are too low or too high to represent real situations in human bodies, the corresponding data are removed from the dataset.

Fig. 4 shows a sample "clean" waveform obtained from data acquired from a real patient during 1 min. On it, signal peaks can be clearly identified, allowing instantaneous heart rate to be accurately estimated as the inverse of the time lapse between two consecutive peaks. This fact has been validated by extensively comparing the heart rates measured with the wearable device with those obtained using a Holter monitor, which is the most accurate way of measuring heart rate over long periods of time. The good correlation between both types of measurements can be noticed in Fig. 5.

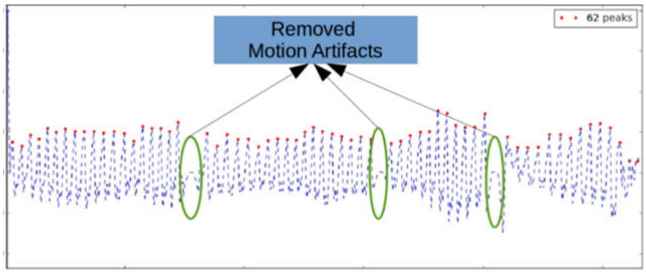

Fig. 4. Sample 1-min "clean" PPG waveform with peak detection.

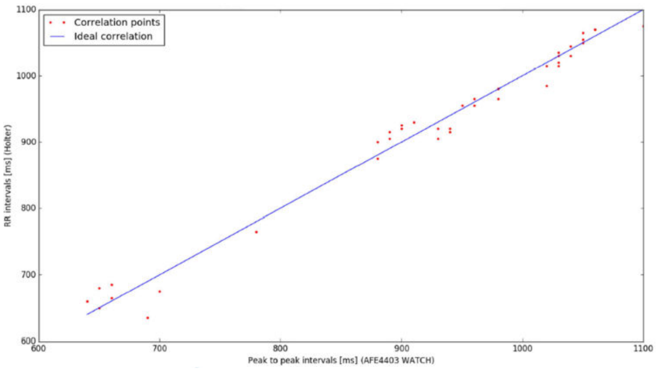

Fig. 5. Correlation between ECG and PPG heart rate measurements.

III. SVMs and Heart Rhythm Classification

SVMs are supervised learning classification algorithms that generate separators (hyperplanes) for input samples, either in their original space (when they are separable or quasi-separable on it) or using the so-called kernel functions (when they are not). The main idea behind SVMs is to find a hyperplane that is equidistant from the closest samples of the different classes, either in the original space or in a higher dimension one defined with the kernel technique. Hyperplanes are defined from training samples on the borders of the target classes, which are called support vectors. Today, SVMs find application in many areas, such as computer vision, speech recognition, or image recognition, to name a few.

In this case, the goal is to classify heart rate data obtained from PPG signals as corresponding to sinus rhythm or atrial fibrillation. In order for such classification to be performed, after capturing and cleaning PPG signals as described in Section II-B to obtain waveforms similar to the one shown in Fig. 4, the following procedure is carried out:

1) Instantaneous heart rate is estimated from the peaks detected in the waveform. Too high or too low heart rate values that cannot correspond to real human body behavior are discarded.
2) Features are then extracted from the remaining data. The selection of the features to be extracted is a key step of the process, because classification results are dependent to a large extent on them. The ones used in this work are described in Section IV.
3) Data are split in two sets, for training and evaluation purposes, respectively, so the proposed approach can be validated. Prior to that, data sequences corresponding to sinus rhythm and atrial fibrillation are identified from electrical cardioversion procedures, as described below.

Electrical cardioversion is a usual procedure for restoring sinus rhythm in patients experiencing atrial fibrillation. It consists in applying to the heart an electric current (called countershock) using a defibrillator. This electric shock does not need to be synchronized with the cardiac cycle. It depolarizes large portions of heart muscle, resulting in the arrhythmia being stopped and the heart recovering sinus rhythm. When this procedure is carried out in the hospital, both ECG and PPG signals can be simultaneously acquired, and the different rhythms (sinus or atrial fibrillation) can be easily identified in the ECG signal and then correlated with PPG data. Patients' informed consent and approval from the Health Service's Ethics Committee were obtained for the acquisition and use of these data for the purposes of this work.

IV. Experimental Validation

In this section, results of heart rhythm classification from data gathered from 11 random patients subject to electrical cardioversion are presented and analyzed. PPG data are sampled at 100 Hz and temporarily stored in the wearable device. Once the electrical cardioversion is completed, data are downloaded to a PC for classification using Matlab® scripts. After preprocessing them, those considered valid are identified (by correlation with ECG data) as corresponding to sinus rhythm or atrial fibrillation, respectively, resulting in the values listed on Table I.

Table I
Valid Data Times for 11 Patients Subject to Cardioversion

Patient	Atrial Fibrillation Time	Sinus Rhythm Time
#1	00:10:05	00:09:10
#2	01:11:30	00:13:15
#3	00:12:15	00:08:00
#4	00:08:20	00:08:10
#5	00:07:05	00:16:25
#6	00:41:45	00:05:15
#7	00:19:30	00:08:00
#8	00:04:45	00:09:01
#9	00:11:20	00:21:00
#10	00:14:25	00:23:35
#11	01:19:05	00:09:55
Total	04:40:05	02:11:46

For feature extraction, valid data are divided in 10s intervals, which are analyzed as independent events. Signal characteristics in both the time and frequency domains have been selected as features to be extracted from the valid datasets:

1) Statistical parameters of the peak-to-peak time distribution: maximum, minimum, mean, and median values, as well as variance, asymmetry, and kurtosis.
2) Parameters of the coefficients of the discrete wavelet transform (using the Daubechies family of wavelets [17]): mean absolute value, average energy, and standard deviation.
3) Shannon entropy [18]. First, the amplitude histogram of each 10s data interval is obtained and divided in several levels depending on the maximum and minimum values of the signal. Then, the Shannon entropy is computed.

After splitting data in training and evaluation sets, different SVM kernels have been tested: linear, quadratic, cubic, and Gaussian. First, to select the most suitable Daubechies wavelet for extracting features in this particular application, several of them have been used to classify heart rhythms with a SVM linear kernel. From a cross validation with 5 iterations, results were obtained in terms of true positive (TPR) and false negative (FNR) rates for the two rhythms. By analyzing the results for each individual patient, significant differences were observed in sinus rhythm classification. To make these differences clear, patients were divided in three groups, A to C (consisting of 2, 3, and 6 patients) according to the similarity of the results obtained for them, summarized in Tables II to IV. In spite of the differences among tables, it can be concluded that db2 is the wavelet providing the best results and, as such, it is the one selected for feature extraction in the frequency domain.

TABLE II
RESULTS FOR GROUP A (DATA FROM 2 PATIENTS)

	Sinus Rhythm		Atrial Fibrillation	
Wavelet	**TPR**	**FNR**	**TPR**	**FNR**
db1	99.8%	0.02%	97.7%	2.3%
db2	99.8%	0.02%	97.7%	2.3%
db3	99.8%	0.02%	97.2%	2.8%
db4	99.8%	0.02%	96.8%	3.2%
db5	99.8%	0.02%	96.8%	3.2%
db6	99.7%	0.03%	96.8%	3.2%

TABLE III
RESULTS FOR GROUP B (DATA FROM 3 PATIENTS)

	Sinus Rhythm		Atrial Fibrillation	
Wavelet	**TPR**	**FNR**	**TPR**	**FNR**
db1	66.2%	33.8%	99.0%	1.0%
db2	66.5%	33.5%	99.0%	1.0%
db3	66.4%	33.6%	99.1%	0.9%
db4	66.5%	33.5%	98.9%	1.1%
db5	66.3%	33.7%	99.0%	1.0%
db6	66.5%	33.5%	99.0%	1.0%

TABLE IV
RESULTS FOR GROUP C (DATA FROM 6 PATIENTS)

	Sinus Rhythm		Atrial Fibrillation	
Wavelet	**TPR**	**FNR**	**TPR**	**FNR**
db1	86.9%	13.1%	92.0%	8.0%
db2	86.5%	13.5%	92.2%	7.8%
db3	86.1%	13.9%	92.0%	8.0%
db4	86.1%	13.9%	92.0%	8.0%
db5	85.8%	14.2%	92.6%	7.4%
db6	85.2%	14.8%	92.3%	7.7%

Once this selection has been made, the cross validation with 5 iterations is carried out using all the remaining aforementioned SVM kernels. The corresponding results are listed on Table V, showing that the best overall results are achieved with the cubic and fine Gaussian kernels.

TABLE V
RESULTS FOR ALL PATIENTS USING DIFFERENT SVM KERNELS

	Sinus Rhythm		Atrial Fibrillation	
SVM Kernel	**TPR**	**FNR**	**TPR**	**FNR**
Linear	68.8%	31.2%	97.9%	2.1%
Quadratic	69.7%	30.3%	99.3%	0.7%
Cubic	79.9%	20.1%	97.3%	2.7%
Fine Gaussian	78.0%	22.0%	98.3%	1.7%
Medium Gaussian	68.8%	31.2%	99.4%	0.6%

These results clearly demonstrate that atrial fibrillation episodes can be correctly identified from PPG signals with more than 97% accuracy, whereas for sinus rhythm results are not as good, ranging from 68.8 to 79.9%. This is mainly caused by the low figures achieved for sinus rhythm in patients from group B, regardless of the kernel used. A detailed analysis of PPG data in this group of patients is currently been conducted to find the reason for the differences and consequently making the changes required to eliminate them, by improving signal preprocessing or choosing different / additional features to be extracted. Even so, achieving more than 97% and nearly 80% accuracy in atrial fibrillation and sinus rhythm classification, respectively, are very promising results that point to the suitability of the proposed solution for affordable ambulatory screening of patients.

V. CONCLUSION

In this paper an affordable solution for ambulatory screening of atrial fibrillation has been presented and validated. It is based on the use of SVMs to classify the huge amount of data that need to be analyzed in such application. Data are gathered from a wearable device that enables biometric signal monitoring at a large population scale.

Features are extracted in both the time and frequency domains. In the latter, the use of the Daubechies family of wavelets has been tested, and the most suitable wavelet from this family in this context has been identified.

Several SVM kernels have also being evaluated. Results obtained with data gathered from real patients demonstrate that cubic and fine Gaussian kernels provide excellent results (above 97% accuracy) for atrial fibrillation classification, and promising ones (close to 80% accuracy) for sinus rhythm classification.

It has been detected that sinus rhythm is very accurately classified for some patients, but not for others. Efforts are currently been devoted to find the reason for this and to consequently improve signal preprocessing or feature extraction to get better results.

It is important to recall that this paper focuses on the analysis of *clean* PPG signals. Patients subject to electrical cardioversion in hospital (which are the ones whose data have been analyzed) are at rest, so the amount of artifacts in PPG signals caused by patients' movement is very low. Work is also been conducted on PPG data acquisition and preprocessing, aimed at obtaining valid information from moving patients, so they can be monitored over long periods of time during their normal life.

The classifier may be improved by including in the analysis data from other sensors (e.g., the gyroscope) available in the wearable device, as well as by extending the number of features extracted from signals, or by using wavelet families others than Daubechies.

A more detailed analysis of the results in terms of sensibility and specificity will be conducted, because these are the usual parameters required to validate a given technique in a medical context.

Finally, the use of other types of classifiers will be a subject of future work.

ACKNOWLEDGMENT

This work was supported by the European Commission under the 7th Framework Programme, FP-7-REGPOT 2012-2013-1 through BIOCAPS (Biomedical Capacities Support Program) grant agreement no. FP7-316265 and by Ministerio de Economía y Competitividad, Spain, under Project TEC2014-56613-C2-1-P.

REFERENCES

[1] R. Fernández Molanes, J. Fariña, J.J. Rodríguez-Andina, and M.Portela, "Design of a muscle activity monitor for rehabilitation of post-stroke patients", in *Proc. 2015 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1427-1432, 2015.

[2] S.E.Stahl, H.-S.An, D.M.Dinkel, J.M.Noble, and J.-M.Lee, "How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough?", *BMJ Open Sport & Exercise Medicine*, Apr. 2016.

[3] P.Kirchhof *et al.*, "2016 ESC Guidelines for the management of atrial fibrillation developed in collaboration with EACTS", *European Heart Journal*, vol. 37, no. 38, pp. 2893–2962, Oct. 2016.

[4] S.S.Chugh, R.Havmoeller, K.Narayanan, D.Singh, M.Rienstra, E.J. Benjamin, R.F.Gillum, Y.-H.Kim, J.H.McAnulty, Z.-J.Zheng, M.H. Forouzanfar, M.Naghavi, G-A.Mensah, M.Ezzati, and Ch.J.L.Murray, "Worldwide epidemiology of atrial fibrillation. A global burden of disease 2010 Study", *Circulation*, vol. 129, pp. 837-847, 2014.

[5] K.G.Tarakji, O.M.Wazni, T.Callahan, M.Kanj, A.H.Hakim, K.Wolski, B.L.Wilkoff, W.Saliba, and B.D.Lindsay, "Using a novel wireless system for monitoring patients after the atrial fibrillation ablation procedure: The iTransmit study", *Heart Rhythm*, vol. 12, no. 3, pp. 554-559, Mar. 2015.

[6] Z.C.Haberman, R.T.Jahn, R.Bose, H.Tun, J.S.Shinbane, R.N.Doshi, P.M.Chang, and L.A.Saxon, "Wireless smartphone ECG enables large-scale screening in diverse populations", *Journal of Cardiovascular Electrophysiology*, vol. 26, no. 5, pp. 520-526, May 2015.

[7] J.Lee, B.A.Reyes, D.D.McManus, O.Mathias, and K.H.Chon, "Atrial fibrillation detection using an iPhone4S", *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 1, pp. 203-206, Jan. 2013.

[8] E.Jo, K.Lewis, D.Directo, M.J. Kim, and B.A.Dolezal, "Validation of biofeedback wearables for photoplethysmography heart rate tracking", *Journal of Sports Science and Medicine*, vol. 15, pp. 540-547, Aug. 2016.

[9] C.McCarthy, N.Pradhan, C.Redpath, and A.Adler. "Validation of the Empatica E4 wristband", in *Proc. 2016 IEEE EMBS International Student Conference*, 2016.

[10] J.Allen, "Photoplethysmography and its application in clinical physiological measurement", *Physiological Measurement*, vol. 28, no. 3, pp. R1-R39, Mar. 2007.

[11] L.F.Polanía, L.K.Mestha, D.T.Huang, and J.P.Couderc, "Method for classifying cardiac arrhythmias using photoplethysmography", in *Proc. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 6574-6577, 2015.

[12] A.Sološenko, A.Petrėnas, and V.Marozas, "Photoplethysmography-based method for automatic detection of premature ventricular contractions", *IEEE Transactions on Biomedical Circuits and Systems*, vol. 9, no. 5, pp. 662-669, Oct. 2015.

[13] K.Amarasinghe, P.Sivils, and M.Manic, "EEG feature selection for thought driven robots using evolutionary algorithms", in *Proc. IEEE 9th International Conference on Human System Interaction (HSI 2016)*, pp. 355-361, 2016.

[14] M.Manic, D.Wijayasekara, K.Amarasinghe, and J.J.Rodríguez-Andina, "Building energy management systems: The age of intelligent and adaptive buildings", *IEEE Industrial Electronics Magazine*, vol. 10, no. 1, pp. 25-39, Mar. 2016.

[15] V.Kecman, *Learning and Soft Computing: Support Vector Machines, Neural Networks, and Fuzzy Logic Models*, MIT Press, 2001.

[16] SVTronics, Inc., *AFE4403 Watch EVM Development Guide*. Available at https://svtronics.com/med/AFE4403%20/AFE4403-HREVM

[17] I.Daubechies, "Ten lectures on wavelets", *CBMS-NSF Regional Conference Series in Applied Mathematics*, vol. 61, SIAM, 1992.

[18] N.Selvaraj, Y.Mendelson, K.H.Shelley, D.G.Silverman, and K.H.Chon, "Statistical approach for the detection of motion/noise artifacts in Photoplethysmogram", in *Proc. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 4972-4975, 2011.