ECG Biometrics: Principles and Applications

Hugo Silva[1], André Lourenço[1,2], Filipe Canento[1], Ana Fred[1] and Nuno Raposo[3]
[1]*Instituto de Telecomunicações, IST-UTL, Lisbon, Portugal*
[2]*DEETC, ISEL-IPL, Lisbon, Portugal*
[3]*Escola Superior de Saúde, Cruz Vermelha Portuguesa, Lisbon, Portugal*

Keywords: Electrocardiography, Identity Recognition, Biometrics, Biosignal Processing.

Abstract: Electrocardiographic (ECG) signals have several properties that can greatly complement the existing, and more established biometric modalities. Some of the most prominent properties are the fact that the signals can be continuously acquired using minimally intrusive setups, are not prone to produce latent patterns, and provide intrinsic liveliness detection, opening new opportunities within the area of biometric systems development. The potential impact of this technique extends to a broad variety of application domains, ranging from the entertainment industry, to digital transactions. In this paper, we present a framework for ECG biometrics, with focus on some of the latest developments and future trends in the field, covering multiple aspects of the problem with the aim of a real-world deployment. Our results so far, further reinforce the feasibility and interest of the method in a multibiometrics approach.

1 INTRODUCTION

Biometrics is an increasingly growing multibillion dollar market; a recent report by Global Industry Analysts, Inc. (Global Industry Analysts, 2011), estimates that by 2017 revenues will grow above $16 billion USD.

User recognition techniques, either in an authentication or identification framework, are generally classified according to their operating principle (Jain et al., 2011), namely: a) What the person knows (e.g. passwords); b) What the person has (e.g. identity card); c) What the person appears to be (e.g. face); and d) What the person does (e.g. voice). The later two methods are generally framed in the area of biometric recognition which, in the current state-of-the-art, includes different types of physical (e.g. fingerprint or iris) and behavioral traits (e.g. signature or keystroke dynamics), among others.

Despite the fact that biometric systems are highly advantageous for user recognition, as they provide information which is more directly related to intrinsic characteristics of the individual, most of the traits currently in use today are only practical for momentary, single validation recognition operations, within a reasonably large time frame. For example, techniques that rely on the fingerprint and/or hand geometry, require the user to place or pass the finger and/or hand in a specific way through a physical reader; techniques that rely on the iris, require the user to stand in a specific physical space, and to have the eye in line of sight with the reader; these and other constraints ultimately limit the scope of application.

The unique properties of ECG signals, are particularly interesting in a multibiometrics approach, either as a security enhancement layer in hard biometrics systems, or as a standalone soft biometrics for low security and low user throughput applications. More importantly, as it can be continuously measured, it enables a new class of applications benefitting from the continuous biometric perspective. In this paper we present a framework for ECG biometrics, covering the essential building blocks; experimental results have been performed, which further reinforce the interest of the ECG-based methods both in an identification and authentication approach.

The remainder of the paper is organized as follows. Sections 2 and 3, present a brief overview of the state-of-the-art and base principles of Electrocardiography (ECG). The proposed approach is described throughout Sections 4, 5, and 6, where the sensor design, signal processing, and biometric recognition steps are presented. Experimental results are summarized in Section7, and finally we highlight discussion topics and outline the main conclusions in Sections 8 and 9.

Silva H., Lourenço A., Canento F., Fred A. and Raposo N..
ECG Biometrics: Principles and Applications.
DOI: 10.5220/0004243202150220
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2013), pages 215-220
ISBN: 978-989-8565-36-5

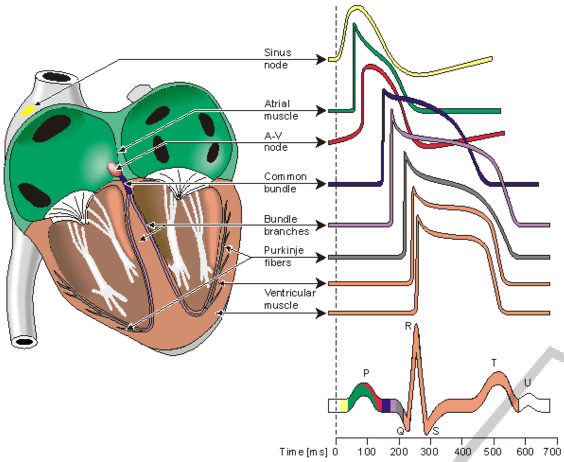


Figure 1: Waveforms of each specialized cells found in the heart (Malmivuo and Plonsey, 1995).

2 STATE-OF-THE-ART

Recent work has been devoted to the characterization of ECG features for human identification, and experimental results have highlighted their discriminating capacity. Still, studies have focused on the offline processing of clinical-grade ECG in an on-the-person approach, with multiple measurement leads. Biel et al. (Biel et al., 2001) were precursors in the field; in their initial work a 12-lead setup was used, and with 10 fiducial features the authors reported 100% accuracy in identification for a population of 20 subjects.

Shen et al. (Shen et al., 2002) experimented on a group of 20 subjects from the MIT/BIH database (Goldberger, A. *et al.*, 2000); they achieved 100% accuracy using a combination of template matching and neural networks. Other experiments were performed by (Israel et al., 2005) on data from 29 subjects; signals were collected at the chest and neck, and 12 latency and amplitude features were used. Using LDA, individual waveforms are classified and mapped to the identity of the subject by majority voting, leading to 100% identification rates.

Research to date has mostly neglected the specificities of real-world application scenarios and acceptability by the potential end users, which pose several constraints and research questions. In the work by (Silva et al., 2007), the authors have concluded that a single lead setup suffices; using a V_2 chest placement, an identification accuracy of 100% was achieved. Later, a palmar placement has been shown to perform accurately in the work by (Lourenço et al., 2011), where for a group of 16 users, even with considerably noisier signals, recognition rates of 94.3% for identification and an Equal Error Rate (EER) of 10.1% are still achieved.

3 PRINCIPLES OF ECG

To accomplish its function, which is basically to pump blood to the pulmonary and systemic circulation, the heart generates electrical current, by the contraction of its muscle cells. Some of these are specialized; the conduction system. These cells have the capability of self-stimulation, which generates the cardiac rhythm, usually a regular sequence of heart beats.

The electrical conduction system of the heart is composed by the sinoatrial node (SA node) that normally initiates the cardiac cycle, the atrioventricular node (AV node), the internodal atrial pathways, which connect the two and regulate the passage of the cardiac impulse from the atria to the ventricles, and the bundle of His and corresponding branches, which in turn are terminated by the Purkinje fibers (Chung, 2000; Malmivuo and Plonsey, 1995). This system enables the electrical triggering impulses generated at the SA node, to be propagated from the wall of the right atrium (where the SA node is located), to the deeper tissues of the ventricular muscles (through where the Purkinje fibers are spread).

The ultimate result of this overall bioelectrical action is the heartbeat. Figure 1 depicts the contribution of each specialized group of cells to the heartbeat waveform (Malmivuo and Plonsey, 1995). The depolarization of the atria generates an ECG wave (P wave), followed by the QRS complex, which represents the ventricular contraction. The end of the cardiac cycle is the cell repolarization phase, which appears as another deflection, the T wave; in some cases, the a second deflection may appear, the U wave.

When measured non-invasively, the ECG records the combined contribution of each component of the electrical conduction system, as propagated to the body surface, and which is expressed as the typical P-QRS-T complexes; this effect alone favors the existence of subject-dependent information, due to the size, shape, and position of the heart within the chest cavity, which varies amongst individuals. However, other factors such as tissue conductivity, genetic singularities, congenital disorders, and heart conditions, constitute additional information sources.

Figure 2 illustrates the ECG while at rest, from two different subjects without any reported heart condition. The plotted individual waveforms y_i were normalized to the mean wave $\bar{x}$ computed from the original segmented heartbeat waveforms x_i (eq. 2) and clipped for better visual understanding. Both subjects

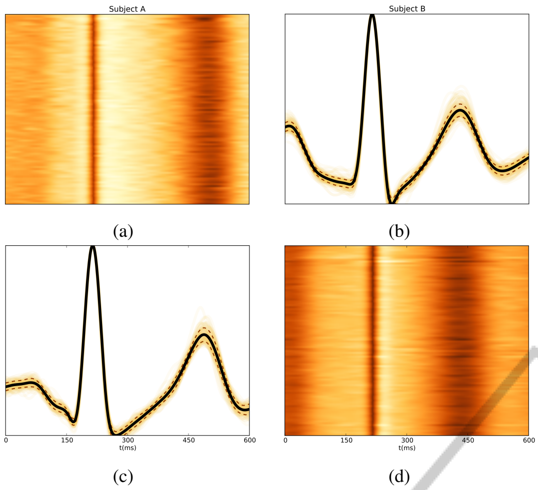


Figure 2: Electrocardiographic recordings from two different subjects while at rest, where the time series were processed to extract one hundred individual heartbeat waveforms, which were then clipped and scaled to fit to the same XX and YY axis limits for better comparison. Figures 2(b) and 2(c) depict the individual waves overlapped, with a solid line representing the mean wave, and a dashed line representing the standard deviation. Figures 2(a) and 2(d) depict a color-map plot, where each line corresponds to an individual heartbeat wave form, and each column represents the amplitude value of a sample; in the color-map, the signal was smoothed around the R peak to enhance the color intensities in the remaining signal.

exhibit morphologically distinct waveforms, with a low intersubject variability; the intensity map of the segmented heartbeat waveforms, showing their temporal evolution, further enhances the differences.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

$$y_i = \frac{x_i - min(\bar{x})}{max(\bar{x}) - min(\bar{x})} \tag{2}$$

Amongst other singularities, in these two cases, the P-Q and S-T curves and latency are significantly distinct; the relative amplitude P-T also varies between subjects. Comparing the ECG of Subject A and B, we observe for example that the bundle branches and Purkinje fibers have a lower activation amplitude in Subject B, or that the AV node recovery time is lower in Subject A.

The fact that there are subject dependent features in the ECG, enhances its applicability for user recognition. Furthermore, the ECG has unique properties when looked at in a multibiometrics approach; in particular, it is: a) universally available in live subjects; b) measurable non-intrusively using suitable devices; c) acceptable due to the latest advances in the sensing technologies; d) not easily circumvented through latent patterns.

4 SENSOR DESIGN

Conventional clinical-grade ECGs are acquired using 12 or more leads mounted on the chest and limbs, using conductive paste or gel to lower the electrode/skin impedance. Part of our work has focused on extending the state-of-the-art, improving current methods by developing a sensor for signal acquisition at the hand palms or fingers. We focused on minimizing the number of electrical contact points with the subject's body, eliminating the need for any gel or conductive paste in the interface with the skin, and devising a non-intrusive sensor design for wearable devices and end-user applications.

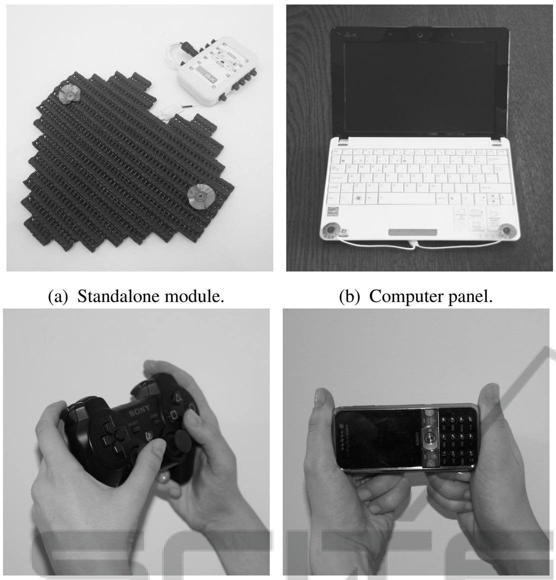
A pseudo V_1 bipolar sensor with virtual ground and dry electrodes was created, consisting of: a) a differential amplifier with gain 10, input impedance $> 1M\Omega$, and $110dB$ CMRR; b) two passive analog filtering steps composed by a $[0.05;100]Hz$ band pass filter, and a notch filter to cut off the $50Hz$ power line interference; and c) a second amplification stage with gain 100 to obtain higher resolution from the collected signal. The sensor has only two contact points with the subject, and works with standard pre-gelled, dry Ag/AgCl, or conductive textile electrodes.

Experimental results have shown that this setup provides an adequate signal quality and biometric performance, even when compared with a more traditional chest setup (Silva et al., 2011; Lourenço et al., 2011). In the overall, we follow a novel off-the-person approach, thus making the usability and intrusiveness comparable to the one found in other biometric traits (e.g. fingerprint). Figure 3 shows the prototype sensor, which can be used as a standalone module, or integrated into everyday objects.

5 SIGNAL PROCESSING

5.1 Filtering

As measured at the body surface, ECG signals are affected by multiple noise sources such as motion artifacts, and power line or electromyographic noise; this aspect is event more challenging in the proposed off-the-person approach, where the impedance between the electrode and the skin is significantly higher due to the lack of gel. We designed a digital zero-phase forward and reverse Butterworth band pass filter with $1-30Hz$ cutoff frequencies, to limit the bandwidth



(a) Standalone module. (b) Computer panel.

(c) Video game controller. (d) Mobile device.

Figure 3: Sensor integration possibilities of the proposed approach.

of the raw data. Note that whereas for clinical applications, a larger passing band is required to preserve additional fiducia, for biometrics we can optimize the filtering taking into account the recognition accuracy.

5.2 Segmentation

Our classifier is based on template matching, using the informative content of the heartbeat waveforms, and as such, a compatible real-time segmentation algorithm is adopted. We build on the work by (Engelse and Zeelenberg, 1979) for offline QRS detection, and propose a combination strategy that uses adaptive thresholds estimated along the acquisition process, according to the methodology and estimation scheme described in (Christov, 2004; Christov and Stoyanov, 2002). A comprehensive description of our proposed approach and comparison between offline and real-time approaches can be found in (Lourenço et al., 2012), where the proposed real-time approach has shown to be competitive. On the ECG biometric point of view, these algorithms represent an important contribution towards the real-world deployment.

6 BIOMETRIC RECOGNITION

6.1 Feature Extraction

All segmented heartbeat waveforms are aligned by their R-peak, and clipped taking into account the typical physiological latencies between the P-R and R-T complexes, which are approximately 200 and 400 milliseconds respectively (Chung, 2000). In this paper, the feature vector for each heartbeat waveform i, consists of a vector x_i with the waveform amplitude values, which corresponds to 600ms of collected signal. During the enrollment stage, the patterns x_i are stored in the database of known users, whereas in the recognition stage, it is the pattern which will be checked against the database. Depending on the latency requirements of the application, we can also use an average of m feature vectors, which is prone to further improve the recognition rates.

6.2 Classification

We use an instance-based learning, template matching approach, through a 1-NN classifier, by computing the similarity between the feature vectors x_u extracted in the recognition phase, and the ones extracted and stored on the enrollment phase, x_i. The decision on a genuine/impostor (authentication task), is determined by verifying if the Euclidean distance $D(x_u,x_i)$, is below an acceptance threshold, computed from the database of enrolled users. For identification, the dissimilarities between the observed pattern x_u and the templates from all enrolled users are computed, and the user identity $\hat{w}_u$ is estimated as the class w_i corresponding to the pattern x_i with lower distance $D(x_u,x_i)$, that is, $\hat{w}_u = w_i : i = \underset{i}{\operatorname{argmin}}(D(x_u,x_i))$.

7 EXPERIMENTAL EVALUATION

Tests were performed on 32 healthy individuals (25 males) with 31.1 ± 9.46 years, using the proposed sensor setup. Subjects were asked to rest their left/right hands over the sensor leads, and data was acquired during a period of approximately 1m30s, during which the experiment supervisor explained the purpose of the study. Raw signals were processed according to the proposed approach, separated into a training set with 30% of the total collected patterns, and a test set with the remaining 70% of the patterns.

We evaluated the user recognition potential of ECG signals collected at the hand palms using directly the individual heartbeat waveforms directly, and also the mean waves computed from a variable number, m, of waveforms. The template matching technique is extremely lightweight in terms of real-time processing, and the mean waves reduce the pattern variability, which is particularly suitable in a real-time framework.

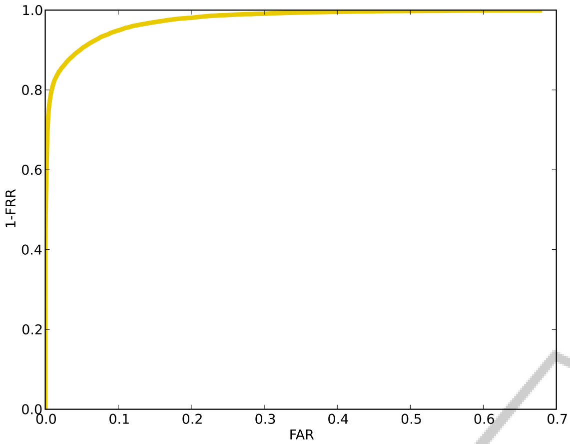


Figure 4: ROC curve for the $m = 5$ best case scenario; m denotes the number of waves used to compute the mean wave.

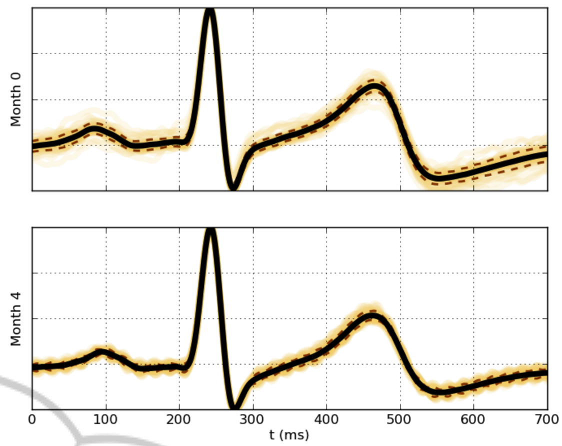


Figure 5: Example of signals collected on two different moments in time (approximately 4 months appart).

Table 1 shows the Equal Error Rate (EER) for authentication and Identification Error (EID) varying the number of patterns m used on the computation of the mean waves. When individual heartbeat waveforms are used, a mean EER of $9.39\% \pm 0.19$ is obtained in authentication, which decreases to $2.75\% \pm 0.29$ when averages of 5 waveforms are used; for identification, a mean EID of $17.62\% \pm 0.59$ is obtained using individual heartbeat wave forms, which decreases to $5.61\% \pm 0.94$, when averages of 5 waveforms are used. The 1 and 5 heartbeats cases correspond, respectively, to $1s$ and $5s$ of acquired signals. The Receiver Operating Characteristics (ROC) curve for the $m = 5$ best case scenario, is presented in Figure 4.

Our results hold comparable performance when matched to other modalities; even when compared to previous ECG based approaches. Table 2, summarizes the user recognition results typically found in the literature for other biosignal based modalities (see (Gamboa, 2008) and references therein). Although the traditional V_2 ECG lead approaches achieve higher accuracy levels, our results, besides holding comparable results, also provide a good compromise between performance and acceptability. Our experimental setup provides usability levels similar to those found in the most widespread modalities, and can be easily integrated into everyday use devices without impacting on the users normal activities, potentiating its use in a continuous biometrics framework.

8 DISCUSSION

Experimental evaluation with real-world data, has revealed an EER of $2.75\% \pm 0.29$ in authentication and $5.61\% \pm 0.94$ EID in identification within a group of 32 subjects. Our system can be further optimized de-

Figure 6: Experimental hardware and software prototype.

pending on the application scenarios. In our previous paper (Silva et al., 2012), a variation of the proposed approach was used to evaluate the applicability of our method to in-vehicle driver recognition. An important aspect within ECG biometric systems, which has been marginally covered in the state-of-the-art is the stability of the signals over time. Preliminary results from our work have shown that, in similar acquisition conditions, the heartbeat waveforms retain a great part of their informative content over time. Figure 5, shows an example of two heartbeat waveforms collected with a 4 months interval in one test subject; the waves are normalized by the maximum and minimum value for easier comparison, and as we can observe, both show a high morphological resemblance.

Table 1: EER and EID for the proposed approach over 30 runs where exclusive training and test sets were randomly selected.

m	1	2	3	4	5
EER	$9.39\% \pm 0.19$	$6.05\% \pm 0.36$	$4.55\% \pm 0.41$	$3.13\% \pm 0.41$	$2.75\% \pm 0.29$
EID	$17.62\% \pm 0.59$	$11.94\% \pm 0.96$	$8.71\% \pm 0.85$	$6.72\% \pm 0.82$	$5.61\% \pm 0.94$

Table 2: EER for other behavioral biometric approaches.

Method	Key Stroke	Mouse	Voice	Gait	Eye Gaze	EEG	ECG V_2
EER	$\sim 4\%$	$\sim 10\%$	$\sim 10\%$	$\sim 5\%$	$\sim 5\%$	$\sim 10\%$	$\sim 5\%$

9 CONCLUSIONS

In this paper we have presented an overview of the base principles and applications of ECG biometrics. If we analyze the ECG in a multibiometrics perspective, it sets an important ground for novel biometric applications, especially those related to continuous user recognition. Results so far are encouraging, which have led us to create an initial prototype system (Figure 6). Immediate applications of our technology include scenarios of low security and low user throughput, such as recognition in mobile phones, laptop computers, cable TV interfaces, and user-tuned in-game experience. If combined with other modalities, there are several use cases where the ECG stands as an important add-on. For example high security applications, we can envision scenarios where user recognition is periodically performed using a hard biometrics such as the fingerprint, ECG data is collected simultaneously with the fingerprint to extract a heartbeat waveform template, and after the initial identity validation using the hard biometric modality, the ECG continues to enable the validation of the user.

ACKNOWLEDGEMENTS

This work was funded by Fundação para a Ciência e Tecnologia (FCT) under the grants SFRH/BD/65248/2009 and SFRH/PROTEC/49512/2009, and by the Instituto de Telecomunicações under the grant ”Android Biometric System”.

REFERENCES

Biel, L., Petterson, O., Phillipson, L., and Wide, P. (2001). ECG analysis: A new approach in human identification. *IEEE Transactions on Instrumentation and Measurement*, 50(3):808–812.

Christov, I. I. (2004). Real time electrocardiogram QRS detection using combined adaptive threshold. *Biomed Eng Online*, 3(1).

Christov, I. I. and Stoyanov (2002). Steep slope method for real time QRS detection. *Electrotechniques and Electronics*, pages 13–17.

Chung, E. K. (2000). *Pocketguide to ECG Diagnosis*. Blackwell Publishing Professional.

Engelse, W. A. H. and Zeelenberg, C. (1979). A single scan algorithm for QRS-detection and feature extraction. *Comp. in Cardiology*, 6:37–42.

Gamboa, H. (2008). *Multi-Modal Behavioural Biometrics Based on HCI and Electrophysiology*. PhD thesis, IST-UTL.

Global Industry Analysts, I. (2011). Biometrics - a global strategic business report. *T. Rep. GIA, Inc.*

Goldberger, A. *et al.* (2000). PhysioBank, physiotoolkit, and physionet: Comp. of a new research res. for complex physiologic signals.

Israel, S., Irvine, J., Cheng, A., Wiederhold, M., and Wiederhold, B. (2005). ECG to identify individuals. *Pattern Recognition*, 38(1):133–142.

Jain, A. K., Ross, A. A., and Nandakumar, K. (2011). *Introduction to Biometrics*. Springer.

Lourenço, A., Silva, H., and Fred, A. (2011). Unveiling the biometric potential of Finger-Based ECG signals. *Comp. Intell. and Neuroscience*, 2011.

Lourenço, A., Silva, H., Leite, P., Lourenço, R., and Fred, A. (2012). Real time electrocardiogram segmentation for finger based ECG biometric. In *BIOSIGNALS 2012*, pages 49–54.

Malmivuo, J. and Plonsey, R. (1995). *Bioelectromagnetism: Principles and Applications of Bioelectric and Biomagnetic Fields*. Oxford Press.

Shen, T. W., Tompkins, W. J., and Hu, Y. H. (2002). One-lead ECG for identity verification. In *Proc. of the IEEE EMBS ’02 Conference*.

Silva, H., Gamboa, H., and Fred, A. (2007). Applicability of lead v2 ECG measurements in biometrics. In *Proc. of the Med-e-Tel Forum*.

Silva, H., Lourenço, A., and Fred, A. (2012). In-vehicle driver recognition based on hand ECG signals. In *Proc. of the IUI ’12 Conf.*, IUI ’12.

Silva, H., Lourenço, A., Lourenço, R., Leite, P., Coutinho, D., and Fred, A. (2011). Study and eval. of a single differential sensor design based on electro-textile electrodes for ECG biometrics applications. In *Proc. of the IEEE Sensors Conf.*