# RAVE-08 Abstract

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# Multimodal Physiological Biometric Authentication

A. RIERA, J. LLOBERA, G. RUFFINI
Starlab Barcelona S.L., Barcelona

## *Abstract*

**Please provide one or two sentences providing a basic introduction to the issue at stake in the research.**

Features extracted from electroencephalogram (EEG) and electrocardiogram (ECG) recordings have proven to be sufficiently unique between subjects for biometric applications. We show here that biometry based on these recordings offers a novel way to robustly authenticate/identify subjects.

**A clear statement of the problem specifically covered by the study, and the current state of the art.**

The present paper introduces a method to authenticate people from their physiological activity, concretely the combination of ECG and EEG data.

Several biometric modalities are already being exploited commercially for person authentication: voice recognition, face recognition and fingerprint recognition are among the more common modalities nowadays. But other types of biometrics are being studied as well: ADN analysis, keystroke, gait, palm print, ear shape, hand geometry, vein patterns, iris, retina and written signature [33].

Although these different techniques for authentication exist nowadays, they present some problems. Typical biometric traits, such as fingerprint, voice and retina, are not universal, and can be subject to physical damage (dry skin, scars, loss of voice...). In fact, it is estimated that 2-3% of the population is missing the feature that is required for authentication, or that the provided biometric sample is of poor quality. Furthermore, these systems are subject of attacks such as presenting a registered deceased person, dismembered body part or introduction of fake biometric samples.

New types of Biometrics, such as electroencephalography (EEG) [1, 2, 3, 4, 5, 6, 7, 8, 9, 25] and electrocardiography (ECG) [14, 15, 16, 17 ,18], are based on physiological signals, rather than more traditional biological traits. These have some advantages: Since every living and functional person has a recordable EEG/ECG signal, the EEG/ECG feature is universal. Moreover brain or heart damage is something that rarely occurs, so it seems to be quite invariant across time. Finally it seems very difficult to fake an EEG/ECG signature or to attack an EEG/ECG biometric system.

An ideal biometric system should present the following characteristics: 100% reliability, user friendliness, fast operation and low cost. The perfect biometric trait should have the following characteristics: very low intra-subject variability, very high inter-subject variability, very high stability over time and universality. In the next section we show the general architecture and the global performance of the system we have developed.

**A section beginning with 'Here we show' giving the main result, explaining what new knowledge has been generated.**

In this paper, we present a rapid and unobtrusive authentication/identification method that only uses 2 frontal electrodes (for EEG recording) with another electrode placed on the left wrist (for ECG recording)and all 3 referenced to another one placed at the right earlobe. Moreover the system makes use of a multi-stage fusion architecture, which has been demonstrated to improve system performance.

The EEG/ECG recording device is ENOBIO [23, 24, 32], a product developed at STARLAB BARCELONA SL. It is a wireless 4 channel (plus the common mode) device with active electrodes. It is therefore quite unobtrusive, fast and easy to place. Even though ENOBIO can work in dry mode, in this study conductive gel has been used.

The general schema used is described below:

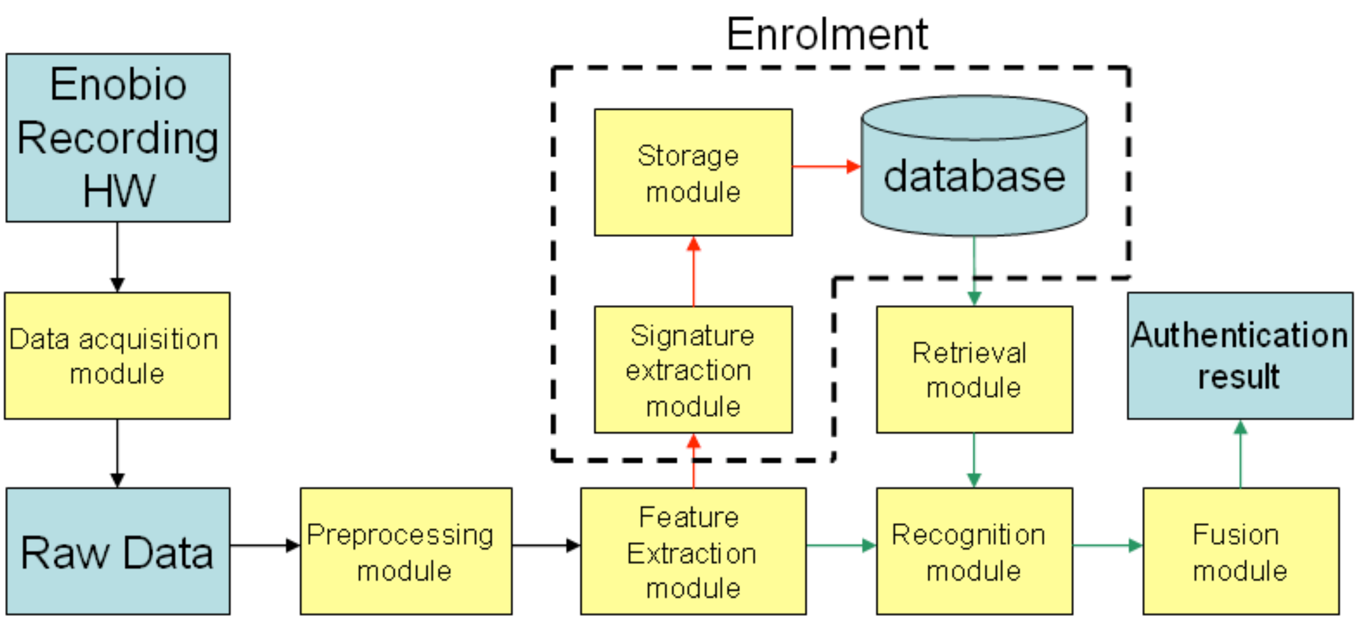


**Figure 1: General scheme of the method. The data acquisition module is the software that controls the ENOBIO sensor in order to capture the raw data. Remember that 4 channels are recorded: 2 EEG channels placed in the forehead, 1 ECG channel placed in the left wrist and 1 electrode placed in the right earlobe for referencing the data. At this point the data is separate in EEG data and ECG data and sent to two parallel but different biometric modules for EEG and ECG (the difference is not shown in the scheme for simplicity). For the signature extraction module, four 3-minutes takes are needed. Once the signatures are extracted, they are both stored in the database for further retrieval when an authentication process takes place. Then the recognition module provides an authentication score for both modalities and finally the fusion module provides the final decision. The enrolment and the authentication test follow a common path until the feature extraction. Then the red arrows indicates the enrolment path and the green ones the authentication path.**

Briefly, the preprocessing module segments the recorded takes into 4 seconds epochs. From each one of those epochs we extract 5 different features: auto-regression coefficients, fast Fourier transform, mutual information, coherence and cross correlation [10, 11, 12, 19, 20, 21]. The classifier used in both the signature extraction module and in the recognition module is the Fisher Discriminant Analysis [13], with 4 different discriminant functions (linear, diagonal linear, quadratic and diagonal quadratic). During the enrolment process, we need four 3-minutes takes, and these are used to select the best combinations of features and classifiers, and then to train the classifiers for each subject. This new feature is what we call 'personal classifier' approach, and it improves the performance of the system considerably. The authentication test takes are 1-minute long. The preprocessing and the feature extraction are equivalent to the enrolment case. The recognition module loads the trained classifiers for each modality (ECG and EEG) and an independent score is then provided for each. Then the fusion module [22] provides a final decision about the subject authentication.

In order to test the performance of our system we use 48 legal situations (when a subject claims to be himself), 350 impostor situations (when an enrolled subject claims to be another subject from the database) and 16 intruder situations (when a subject who is not enrolled in the system claims to be a subject belonging to the database). Once the EEG and the ECG biometrics results are fused, using a complex boundary decision, we can obtain an ideal performance, that is True Acceptance Rate (TAR) = 100% and False Acceptance Rate (FAR) = 0%. If a linear boundary decision is used, we obtain a TAR = 97.9% and a FAR = 0.82%.

This system has been tested as well to validate the initial state of users, and has been proved sensitive enough to detect it. If a subject has suffered from sleep deprivation [28], alcohol intake [26, 27] or drug ingestion when passing an authentication test, the authentication performance decreases. This fact provides evidence that such a system is able to detect not only the identity of a subject but his state as well.

**A section explaining what the main result reveals in direct comparison to what was thought to be the case previously, or how the main result adds to previous knowledge.**

These results show that the authentication of people from physiologic data can be achieved using techniques of machine learning. Concretely it shows that the fusion of two (or more) independent biometric modules increases the performance of the system by applying a fusion stage after obtaining the biometric scores.

This result shows that processing the different physiological modalities separately on different processing modules, and introducing a data fusion step, the resulting performance can be increased. Applying a very similar approach, we could easily adapt the system to do emotion recognition [29, 30, 34] from physiological data, or develop a Brain Computer Interface, just starting from different ground truth data. From our point of view, this easy to extend feature of our system is the more interesting part of our study along with the 'personal classifier' approach which improves considerably the performance of the system.

**A section putting the results into a more general context, and the implications for further research.**

The system described could have different applications for Virtual Reality. It can validate in a continuous way that the person supposed to be tele-present in an audiovisual interactive space is actually the person that is supposed to be. This could facilitate the personalization of the reaction of the virtual environment [31], or secure interactions that guarantee the authenticity of the person behind.

Although the system described here was oriented towards person identification, its performance has been significantly modified by introducing physiological data obtained in altered states such as the ones resulting from sleep deprivation. This indicates that such a system could be used to extract dynamically changing, such as physiological activity related to mood or to intense cognitive activity. For example, it could be used to extract the features described (sleep deprivation, alcohol intake), but also information about basic emotions (see, for example, 0).

The dynamic extraction of such features could be used to evaluate the response of people in virtual environments, as well as adapt the behavior of such environments to the information extracted dynamically.

The advantage that such a system would present compared to currently existing approaches is that –by having built a decisional system that is completely modular- we could estimate each class independently of the other classes obtained, which would allow us to have a modular approach to define the interaction between the human and the machine.

Finally we would like to highlight the usefulness of using a single system for user state monitoring and user personalization. Assuming that the system is worn anyway for physiological feedback, this same system can personalize your experience because it knows who you are without any interaction required by the user.

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1. Eischen S., Luctritz J. and Polish J. (1995) Spectral analysis of EEG from Families. Biological Psycholology,Vol. 41, pp. 61-68.
2. Hazarika N., Tsoi A. and Sergejew A. (1997) Nonlinear considerations in EEG signal Classification. IEEE Transactions on signal Processing, Vol. 45, pp.829-836.
3. Marcel S., Mill J. (2005) Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation. IDIAP Research Report 05-81, 11 pp.
4. Mohammadi G. et al. (2006) Person identification by using AR model for EEG signals. Proc. 9th International Conference on Bioengineering Technology (ICBT2006), Czech Republic,5 pp.
5. Paranjape R. et al.(2001)The electroencephalogram as a biometric. Proc. Canadian Conf. On Electrical and Computer Engineering, pp. 1363-1366.
6. Poulos M. et al. (1998) Person identification via the EEG using computational geometry algorithms. Proceedings of the Ninth European Signal Processing, EUSIPCO'98, Rhodes, Greece. September1998,pp. 2125-2128.
7. Poulos M. et al. (1999) Parametric person identification from EEG using computational geometry. Proc. 6th International Conference on Electronics, Circuits and Systems (ICECS'99),v. 2, pp. 1005-1008.
8. PoulosM.et al. (2001) On the use of EEG features towards person identification via neural networks. Medical Informatics & the Internet in Medicine, v. 26, pp. 35-48.
9. Poulos M. et al. (2002) Person identification from the EEG using nonlinear signal classification. Methods of Information in Medicine,v. 41, pp. 64-75.
10. Remond A., Ed. (1997) EEG Informatics. A didactic review of methods and applications of EEG data processing, Elsevier Scientific Publishing Inc., New York,1997.
11. Sviserskaya N., Korolkova T.(1995)Genetic Features of the spatial organization of the human cerebral cortex. Neuroscience and Behavioural Physiology, Vol.25,N.5,pp. 370-376.
12. Deriche M., Al-Ani A. (2001) A new algorithm for EEG feature selection using mutual information. Acoustics, Speech, and Signal Processing, 2001. Proceedings. '01,pp. 1057 - 1060vol.2
13. Duda R.etal.,PatternClassification, Wiley, New York, 2001.
14. Biel L. et al. (2001) ECG analysis: a new approach in human identification. IEEE Transactions on Instrumentation and Measurement, Vol. 50, N. 3, pp.808-812.
15. Chang C.K. (2005) Human identification using one lead ECG. Master Thesis. Department of Computer Science and Information Engineering. Chao yang University of Technology (Taiwan).
16. Israel S. et al. (2005) EGC to identify individuals. Pattern Recognition, 38, pp.133-142.
17. Kyoso M. (2001) Development of an ECG Identification System. Proc. 23rd Annual International IEEE Conference on Engineering in Medicine and Biology Society, Istanbul, Turkey.
18. Palaniappan R. and Krishnan S.M. (2004) Identifying individuals using ECG beats. Proceedings International Conference on Signal Processing and Communications,2004. SPCOM'04,pp. 569-572.
19. WintererG.et al. (2003) Association of EEG coherence and anexonic GABA(B)R gene polymorphism. Am JMed Genet B Neuropsychiatr Genet,117:51-56.

20. Kikuchi M. et al. (2000) Effect of normal aging upon inter hemispheric EEG coherence: analysis during rest and photic stimulation. Clin Electroencephalogr,31: 170-174.
21. Moddemeijer R. (1989) On estimation of entropy and mutual information of continuous distributions. Signal Processingvol.16nr.3pp.233-246
22. Ross A, Jain A. (2003) Information fusion in biometrics. Pattern Recognition Letters 24pp.2115-2125
23. G. Ruffini et al. (2006) A dry electrophysiology electrode using CNT arrays. Sensors and Actuators A132 34-41
24. G. Ruffini et al. (2007) ENOBIO dry electrophysiology electrode; first human trial plus wireless electrode system. 29th IEEE EMBS Annual International Conference.
25. A. Riera et al. (2007) Unobtrusive Biometric System Based on Electroencephalogram Analysis. EURASIP Journal on Advances in Signal Processing. Volume 2008 (2008), Article ID 143728
26. Hogansetal. (1961)Effects of ethyl alcohol on EEG and avoidance behavior of chronic electrode monkeys. Am JPhysio, 201: 434-436
27. J.Sorbeletal. (1996)Alcohol Effects on the Heritability of EEG Spectral Power alcoholism: clinical and experimental research
28. S. Jin et al (2004) Effects of total sleep-deprivation on waking human EEG: functional cluster analysis. Clinical Neurophysiology, Volume 115, Issue 12, Pages 2825-2833
29. KazuhikoTakahashi(2004)Remarks on Emotion Recognition from Bio-Potential Signals. 2nd International Conference on Autonomous Robots and Agents.
30. A. Haag et al. (2004) Emotion Recognition Using Bio-sensors: First Steps towards an Automatic System. Springer-Verlag Berlin Heidelberg, ADS, LNAI 3068,pp. 36-48.
31. J.Llobera (2007) Narratives within Immersive Technologies. arXiv:0704.2542.
32. G.Ruffini et al. (2006) First human trials of a dry electrophysiology sensor using a carbon nanotube array interface. arXiv:physics/0701159
33. V. Gracia et al. (2006) State of the Art in Biometrics Research and Market Survey. HUMABIO Project (EU FP6 contract no 026990). Deliverable N.1.4.www.humabio-eu.org
34. Rainville, P, Bechara, A, Naqvi, N, Damasio, A. Basic emotions are associated with distinct patterns of cardio respiratory activity. International Journal of psychophysiology 61 (2006)