ISSN 1392 – 1215 ELECTRONICS AND ELECTRICAL ENGINEERING 2009. No. 1(89)
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Detrended Cross-Correlation Analysis of Biometric Signals used in a new Authentication Method

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Introduction

Recent developments in the field of biometrics and cryptography led to the possibility of using electroencephalographic (EEG) signals as biometric keys in cryptographic systems, [1]-[6]. Such a system records the EEG signals, extracts certain features and therefore they are encoded by means of a fuzzy vault, [2]. An authentication system based on EEG signals, or "thoughts" as named in [1], has some potential advantages, like a vast passwords space, the ease of change of the password and the resilience to shoulder surfing. All of that is provided if there is a method to extract that much entropy from the EEG signals, in a repeatable manner. In order to accomplish this task and to develop a commercial system of authentication of this kind, some challenges must be faced. Among them is the variability of the signals, the number of the locations of the scalp that need to be monitored and the features that are appropriate to accomplish the undertaking. In fact, just some features of the EEG signals are useful to be transformed in biometric keys. To extract such features and to be able to avoid unwanted false detections is not an easy task, since the signals are highly nonstationary and therefore any method used for stationary signals needs to be adjusted to fulfill the requirements of the analysis of nonstationary signals. Until now, this was usually achieved considering smaller time intervals and assimilating those signals with the stationary ones.

This paper aims to show how to reduce the amount of points for collecting the EEG signals for an authentication system like the one proposed in [1], based on their correlation properties, and to highlight additional use of the method.

There is another reason to further analyze the time series represented by the EEG signals as nonstationary signals: to establish the possible correlations with other data in certain pathologies.

In what follows, we will review the theoretical background for the algorithm that allows the computing of the detrended cross-correlation function, while the next section is devoted to the characterization of the EEG signals from this point of view. The third deals with the potential implications of the results as an indicator for the brain activities specific to a certain mental task and the last one is committed to the concluding remarks.

Detrended cross-correlation: the algorithm

Cross-correlation is a well-known statistical method used to establish the degree of correlation between two (usually time) series. This is done considering that stationarity characterizes both time series under investigation. Unfortunately, real time series are hardly stationary and to cure that, as a rule, short intervals are considered for analysis. This is not always a valid choice, especially when the time series need to be seen and analyzed as a whole. For this reason a method that deals with nonstationary time series, named detrended cross-correlation analysis, was introduced by Podobnik and Stanley, [7]. We shall recall the main points of the algorithm here, in brief.

The subsequent notations will be used: let $\{x_k\}$ and $\{y_k\}$ be two time series with k=1,2…N, where N is the maximum number of samples. The mean and the variance of the two time series are m_1, σ_1 and m_2, σ_2, correspondingly. We denote generically by

$$A(n) = \frac{1}{\sigma^2}\left(\frac{1}{N}\sum_{k=1}^{N}(x_k - m)\cdot(x_{k+n} - m)\right), \tag{1}$$

the autocorrelation function of the time series $\{x_k\}$ and by

$$X(n) = \frac{1}{\sigma_1\sigma_2}\left(\frac{1}{N}\sum_{k=1}^{N}(x_k - m_1)\cdot(y_{k+n} - m_2)\right), \tag{2}$$

the cross-correlation function of time series $\{x_k\}$ and $\{y_k\}$. We will assume that the autocorrelation functions of $\{x_k\}$ and $\{y_k\}$ and their cross-correlation function scale as power laws:

$$A_1(n) \sim n^{-p_1},\ A_2(n) \sim n^{-p_2},\ X(n) \sim n^{-p_{xy}} \tag{3}$$

with p_1, p_2, $p_{xy} \in (0,1)$.

Let us now define two "integrated" signals, consisting of the sum of *m* successive steps, as follows:

$$S_1(m) = \sum_{k=1}^{m} x_k\ ,\quad S_2(m) = \sum_{k=1}^{m} y_k\ , \tag{4}$$

where $m \le N$. The time series are divided into N-n boxes and therefore each one covers $n+1$ elements of the time series. Let us denote generically such a "box", which starts with m index and finishes with m+n, by $B_{m,n}$.

Using the samples between i and $i+n$ we shall perform a least square fit. Supposing that the equations of the lines obtained for each time series are

$$X = T_1(m,i)\cdot n + S_1(m,i) \tag{5}$$

and

$$Y = T_2(m,i)\cdot n + S_2(m,i)\,, \tag{6}$$

we define the ordinates of the least square fit, $S_1(m,i)$ and $S_2(m,i)$ as "local trends". To detrend the time series, we characterize as residuals the difference between the initial choice and the local trends. For each box $B_{m,n,}$ the covariance of the residuals may be written as

$$x_{dcc}^2(n,i) = \frac{1}{(n-1)}\cdot\sum_{k=i}^{i+n}(S_1(m)-S_1(m,i))\cdot(S_2(m)-S_2(m,i)). \tag{7}$$

Summing over all the boxes we get the detrended covariance, which quantifies long-range cross correlations in the presence of nonstationarities:

$$F_{DCC}^2 = \frac{1}{(N-n)}\sum_{i=1}^{N-n} x_{dcc}^2(n,i). \tag{8}$$

It is worth remembering the fact that when just one time series is used and therefore $S_1(m)=S_2(m)$, the detrended covariance reduces to the detrended variance, as acknowledged in [8].

The data set

The signals that were used in this study were aquisitioned by means of a 10-20 system of electrodes placed on human scalp. A Donchin paradigm, [9], was used to collect the data: the user was presented with a 6 by 6 matrix of characters. Then, the user was asked to focus his attention on characters in a word that was chosen as a password; each character of the word appeared in their initial succession, but in a random manner, as time was concerned. The rows and columns of this matrix were successively and randomly intensified at a rate of 5.7 Hz. and two out of 12 intensifications of rows or columns contained the desired character (one in a particular row and one in a particular column). The responses evoked by these infrequent stimuli are different from those evoked by the stimuli that did not contain the desired character, and they are similar to the P300 responses. So an evoked potential is generated every time the subject of the study encounters a change in the illumination of a row or column that has a letter on which, at the request of the investigator, according to the chosen password, the attention of the subject is focused.

The designation of the electrodes was the one introduced by Sharbrough in [10] and is presented in Fig.1, after the drawing from reference [11].

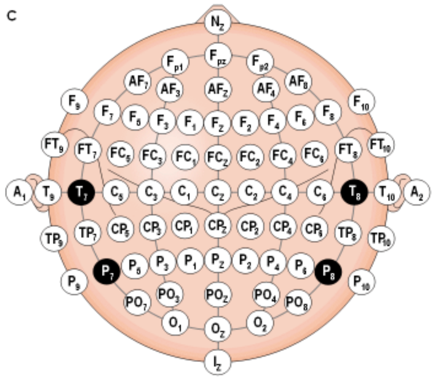

Fig. 1. The electrodes designation for the 10-20 system

Our study was performed for several time series with the average length of 8000 samples and it was a very time consuming task, even for a fast computer. To exemplify the method and to evidence the main results, a smaller sample (10% of the time series) was considered due to clarity and (mostly) graphical reasons. First the detrended variance was computed and it is worth noticing that the p_{xx} coefficient, the one that describes the auto-correlations, showed a large range of variation, from 0.04 for the P_z electrode to 0.986 for the F_8 electrode, as shown in Fig. 2 and Fig. 3.

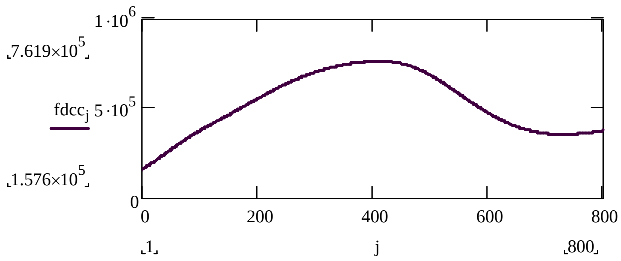

Fig. 2. The detrended covariance for the time series characterizing the P_z electrode: p_{xx}=0.04

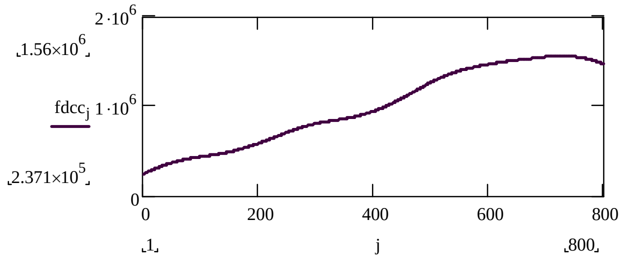

Fig. 3. The detrended covariance for the time series characterizing the F_8 electrode: p_{xx}=0.986

Due to the odd behavior of the autocorrelation functions of the above time series, we shall focus our attention on their cross-correlation properties. First, let us present the integrated signals for the time series collected by means of the AF_z and P_z electrodes in Fig.4. It may be seen that both S_1 (the thin line) and S_2 (the thick line) follow approximately the same shape, but at different scales. This is a typical case of series that exhibit power-law autocorrelations with similar scaling exponents. This may be interpreted as large variations in a time series may lead to the same kind of variations in the other one.

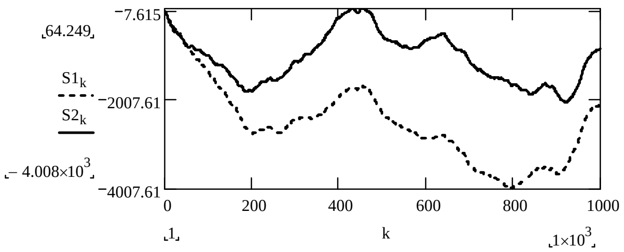

Fig. 4. The integrated signals S_1 and S_2 for the AF_z and P_z electrodes.

The detrended covariance between the AF_z and P_z time series is shown in Fig. 5. It is worth noticing the fact that it resembles the one characterizing Pz, from Fig. 2.

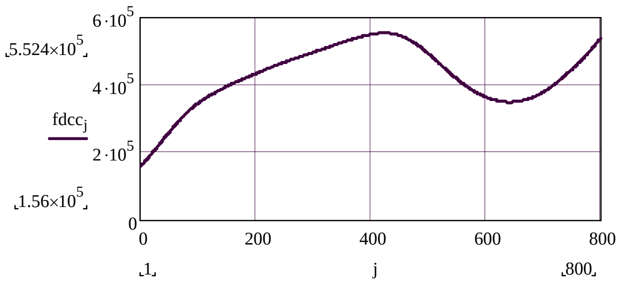

Fig. 5. The detrended covariance between AF_z and P_z signals: the p_{xy} exponent is 0.117

The value of the p_{xy} for the time series represented by the AFz and P_z signals, indicates an anti-correlation behavior, that is large values in one series are followed by smaller ones in the other.

A rather different situation, but nevertheless equally possible, is the one that is shown in Fig. 6 for the integrated signals of the F_7 and F_8 electrodes.

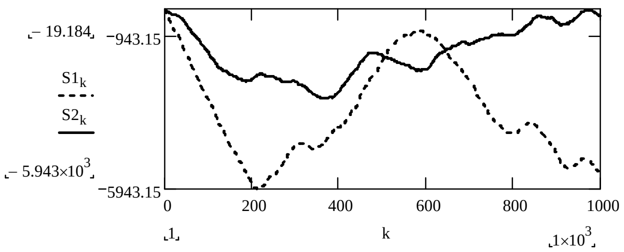

Fig. 6. The integrated signals S_1 and S_2 for the F_7 and F_8 electrodes

The shape of each signal is quite different and as a consequence, this is evidenced in the profile of the detrended covariance and the value of the p_{xy} coefficient in Fig. 7.

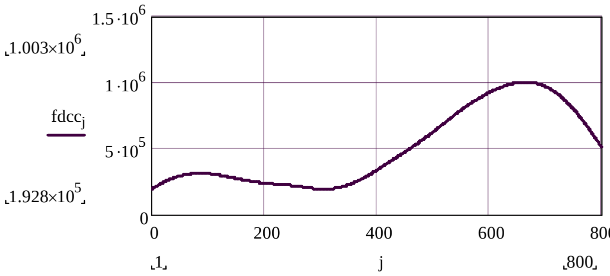

Fig. 7. The detrended covariance between F_7 and F_8 signals: the p_{xy} exponent is 0.74

Using the results of the previous analysis in the authentication method

There are quite a few possibilities to use the results of the detrended cross-correlation analysis in a system that aims to implement the one proposed in [1]. First, it may be of a real help in choosing the right number of electrodes for the cap; one must bare in mind the need to have as less electrodes as possible for a practicable commercial system, since the level of acceptance of the system is closely linked to the less amount of hardware needed to implement it. If the signals from two or more electrodes are correlated, then there is no need to use them all in the feature extraction process. Furthermore, the possibility to quantify the long-range cross correlations by means of the p_{xy} coefficient could be of certain help in the feature extraction process, in case of doubt.

It is worth noticing the fact that, according to our study, not all signals of the electrodes present long range cross correlations, but drawing a "map" of this kind proves to be a difficult task, due to the great variability of the signals.

Conclusion

The study proved to be useful in giving some hints to implement an authenticating system based on electroencephalographic signals. It showed that the algorithm used is suitable to detect both kinds of behavior of the time series represented by different signals collected from diverse electrodes: cross-correlations and anti-correlations. The number of the samples that were analyzed, approximately 8000 for each time series, was large enough to draw the conclusions, since for that amount of data the scaling exponents were evaluated with an error less than 5%.

References

1. **Thorpe J., van Oorschot P. C., Somayaji A.** Pass-thoughts: Authenticating With Our Minds // ACSA 2005 New Security Paradigms Workshop. – Sept. 2005, Lake Arrowhead, California, in Cryptology ePrint Archive: Report 2005/121 (eprint.iacr.org).
2. **Juels A., Sudan M.** A Fuzzy Vault Scheme // Proceedings of IEEE Internation Symposium on Information Theory. – Lausanne, Switzerland: IEEE Press, 2002. – P. 408–412.

3. **Wolpaw J. R., Birbaumer N., McFarlanda D., Pfurtscheller G., Vaughan T.** Brain–computer interfaces for communication and control // Clinical Neurophysiology. – 2002. – Vol. 113. – P. 767–791.
4. **Andrzejak R. G., Lehnertz K., Rieke C., Mormann F., David P., Elger C. E.** Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state // Phys. Rev. E. – 2001. – Vol. 64.
5. **Walpaw J., McFarland D., Vaughan T.** Brain-Computer Interface Research at the Wadsworth Center // IEEE Transactions on Rehabilitation Engineering. – June 2000. – Vol. 8, No. 2. – P. 222–226.
6. **Donchin E., Spencer K. M., Wijensinghe R.** The mental prosthesis: Assessing the speed of a P300-based brain-computer interface // IEEE Transactions on Rehabilitation Engineering. – 2000. – Vol. 8. – P. 174–179.
7. **Podobnik B., Stanley H. E.** Detrended Cross-Correlation Analysis: A New Method for Analyzing Two Non-stationary Time Series // Phys. Rev. Lett. – 2008. – Vol. 100.
8. **Buldyrev S. V., Goldberger A. L., Havlin S., Mantegna R. N., Matsa M. E., Peng C.-K., Simons M., Stanley H. E.** Long-Range Correlation Properties of Coding and Noncoding DNA Sequences: GenBank Analysis // Phys. Rev. E. – 1995. – Vol. 51. – P. 5084–5091.
9. **Farwell L. A., Donchin E.** Talking Off The Top Of Your Head: A Mental Prosthesis Utilizing Event-Related Brain Potentials // Electroencephalography and Clinical Neurophysiology. – 1988. – Vol. 70. – P. 510–513.
10. **Sharbrough F., Chatrian G.-E., Lesser R. P., Lüders H., Nuwer M., Picton T. W.** American Electroencephalographic Society Guidelines for Standard Electrode Position Nomenclature // J. Clin. Neurophysiol. – 1991. – Vol. 8. – P. 200–202.
11. **Malmivuo J., Plonsey R.** Bioelectromagnetism – Principles and Applications of Bioelectric and Biomagnetic Fields // New York: Oxford University Press, 1995.

Received 2008 10 29

R. Ursulean, A.-M. Lazar. Detrended Cross-Correlation Analysis of Biometric Signals used in a new Authentication Method // Electronics and Electrical Engineering. – Kaunas: Technologija, 2009. – No. 1(89). – P. 55–58.

The paper presents a study that aims to facilitate the development of an authenticating method, based on biometric signals. Considering a recently introduced method (2008) called the detrended cross-correlation analysis, the authors showed the long-term correlations and anti-correlations of different electroencephalographic signals, which could lead to a smaller number of electrodes in such an authentication method. The correlation coefficient was computed for different pairs of electrodes, for a large number of samples, leading to an acceptable margin of error. Further work in this field could lead to valuable results in analyzing the EEG signals in different pathologies. Ill. 7, bibl. 11 (in English; summaries in English, Russian and Lithuanian).

Р. Урсулеан, А. М. Лазар. Анализ биометрических сигналов, используемых в новом опознавательном методе, используя нетенденционную взаимную корреляцию // Электроника и электротехника. – Каунас: Технология, 2009. – № 1(89). – С. 55–58.

Представлено исследование, которое стремится облегчить развитие метода подтверждения, основанного на биометрических сигналах. Рассматривая недавно внедренный метод (2008), названный анализом взаимной корреляции, авторы показали постоянные корреляции и антикорреляции различных электроэнцефалографических сигналов, которые могли привести к меньшему числу электродов в таком опознавательном методе. Коэффициент корреляции был вычислен для различных пар электродов, для большого количества образцов и имели небольшие ошибки. Далнейшая работа в этом направлении может дать ценные результаты анализа сигналов электроэнцефалограммы в различных патологиях. Ил. 7, библ. 11 (на английском языке; рефераты на английском, русском и литовском яз.).

R. Ursulean, A. M. Lazar. Biometrinių signalų, naudojamų kuriant naują tapatumo nustatymo metodą, netendencinga tarpusavio koreliacinė analizė // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2009. – Nr. 1(89). – P. 55–58.

Pristatytas tyrimas, kuriuo siekiama palengvinti kurti biometriniais parametrais paremtą tapatumo nustatymo metodą. Autoriai nagrinėja 2008 metais pristatytą netendencingos (angl. detrended) tarpusavio koreliacinės analizės metodą. Parodyta, kad skirtingų elektroencefalografinių signalų ilgalaikio periodo koreliacijos ir antikoreliacijos potencialiai gali leisti tapatumo nustatymo metu naudoti mažiau elektrodų. Esant dideliam matavimų skaičiui gaunamos priimtinos paklaidos. Tolesnis darbas šioje srityje gali duoti vertingų EEG signalų analizės rezultatų tiriant skirtingas patologijas. Il. 7, bibl. 11 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).

DOI: 10.5755/j02.eie.10567