Personal Identification and Authentication based on One-lead ECG using Ziv-Merhav Cross Parsing

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Abstract. In this paper, we propose a new data compression based ECG biometric method for personal identification and authentication. The ECG is an emerging biometric that does not need liveliness verification. There is strong evidence that ECG signals contain sufficient discriminative information to allow the identification of individuals from a large population. Most approaches rely on ECG data and the fiducia of different parts of the heartbeat waveform. However non-fiducial approaches have proved recently to be also effective, and have the advantage of not relying critically on the accurate extraction of fiducia. We propose a non-fiducial method based on the Ziv-Merhav cross parsing algorithm for symbol sequences (strings). Our method uses a string similarity measure obtained with a data compression algorithm. We present results on real data, one-lead ECG, acquired during a concentration task, from 19 healthy individuals, on which our approach achieves 100% subject identification rate and an average equal error rate of 1.1% on the authentication task.

1 Introduction

Biometrics deals with identification of individuals based on their physiological or behavioral characteristics [1]. Traditional methods of biometric identification, include those based on physiological characteristics like fingerprints or iris, and those based on behavioral characteristics like signature or speech. Although some technologies have gained more acceptance than others, the field of biometrics for access control plays an important role in the security at airports, industry and corporate workplaces, for example. But some technologies lack robustness against falsification. Some may be based on such characteristics that for a group of people is difficult to acquire or even that characteristics is missing.

The electrocardiogram (ECG) is an emerging biometric measure which exploits a physiological feature that exists on every human and there is a strong evidence that the ECG is sufficiently discriminative to identify individuals from a large population. The ECG feature allows liveliness detection (intrinsic), personal identification and authentication, and different stress or emotion states detection [2]. The ECG is a behavioral biometric trait that can be used with other biometric measures [3], as a complementary feature, for fusion in a multimodal physiological authentication system [4, Ch. 18] and for continuous authentication where biological signatures are continuously monitored

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(easily done by using new signal acquisition technologies like the Vital Jacket [5], [6]) in order to guarantee the identity of the operator throughout the whole process [7].

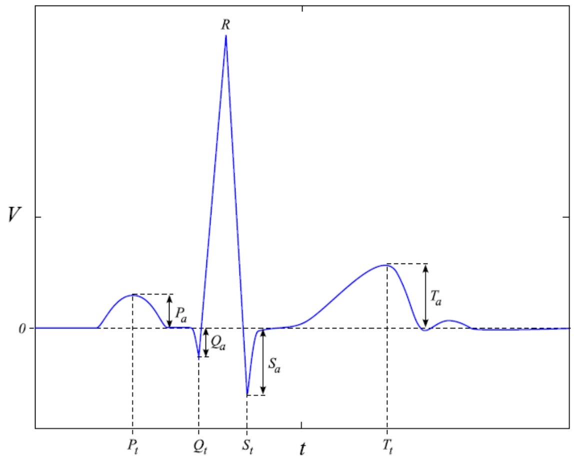

Fig. 1. Example of four latency times (features) measured from the P, QRS and T complexes of an ECG heartbeat for fiducial-based feature extraction.

A typical ECG signal of a normal heartbeat can be divided into 3 parts, as depicted in Fig. 1: the P wave (or P complex), which indicates the start and end of the atrial depolarization of the heart; the QRS complex, which corresponds to the ventricular depolarization; and, finally, the T wave (or T complex), which indicates the ventricular repolarization. It is known that the shape of these complexes differs from person to person, a fact which has stimulated the use of the ECG as a biometric [8].

In a broad sense, one can say there are two different approaches in the literature concerning feature extraction from ECG: fiducial [8], [9], [10], [11], and non-fiducial [12], [13]. Fiducial methods use points of interest within a single heartbeat waveform, such as local maxima or minima; these points are used as reference to allow the definition of latency times, as shown in Fig. 1. Several methods exist that extract different time and amplitude features, using these reference points. Non-fiducial techniques aim at extracting discriminative information from the ECG waveform without having to localize fiducial points. In this case, a global pattern from several heartbeat waveforms may be used as a feature. Some methods combine these two different approaches or are partially fiducial [14] (e.g., they use only the R peak as a reference for segmentation of the heartbeat waveforms).

Biel et al. [8] pioneered the use of the ECG as a biometric for personal identification. They used a 12-lead ECG but ended up concluding that one lead was enough because 12-lead ECG systems require meticulous placement of the electrodes on each person, which is not practical. Using a proprietary equipment from SIEMENS, 30 fiducial features were extracted; a feature selection algorithm allowed concluding that the best results were with 10 features. Classification was based on the principal component analysis (PCA) of each class. The purpose was to identify 20 subjects at rest and they achieved an accuracy of 100%.

Recent studies have shown that non-fiducial approaches also allow successful personal identification using the ECG heartbeat signal.

Chiu et al. [13], using a one-lead ECG, introduced a system based on a 3-step feature extraction method. It uses QRS complex detection (with the So and Chan method [15]) and waveform alignment in the time domain; the features extracted are based on the discrete wavelet transform. A nearest neighbor classifier based on the Euclidean distance between pairs of feature vectors is used. The purpose was to identify 35 subjects (no activity specified) from the QT database [16]. The results obtained were: 100% of accuracy on person identification and 0.83% FAR (false acceptance rate) and 0.86% FRR (false rejection rate) for authentication.

This paper introduces a new non-fiducial ECG-biometric method that uses averaged single heartbeat waveforms and is based on data compression techniques, namely the Ziv-Merhav cross parsing (ZMCP) algorithm for sequences of symbols. We present results on real data, using one-lead ECG acquisition during a concentration task. Notice that a study [2] with the dataset showed the existence of differentiated states in the data representing the ECG signal of a subject due to detectable changes along the time in the acquired signal. On a set of 19 healthy individuals, our method achieves 100% subject identification (recognition) rate and an average equal error rate of 1.1% on the authentication (verification) task.

The outline of the paper is as follows. In Section 2, we review the fundamental tools underlying our approach: Lempel-Ziv string parsing and compression; the Ziv-Merhav cross parsing algorithm. Section 3 presents the proposed classification method. Experimental results are presented in Section 4, while Section 5 concludes the paper.

2 The Lempel-Ziv and Ziv-Merhav Algorithms

The Lempel-Ziv (LZ) algorithm is a well-known tool for text compression [17], [18], [19], [20], which in recent years has also been used for classification purposes (see [21] and references therein). In particular, in [21], we have shown how the Ziv-Merhav (ZM) method for measuring relative entropy [22] (which is based on Lempel-Ziv-type string parsing) achieves state-of-the-art performance in a specific text classification task. We will now briefly review these algorithms.

- The incremental LZ parsing algorithm [18], is a self parsing procedure of a sequence into $c(\mathbf{z})$ distinct phrases such that each phrase is the shortest sequence that is not a previously parsed phrase. For example, let $n = 11$ and $\mathbf{z} = (01111000110)$, then the self incremental parsing yields $(0, 1, 11, 10, 00, 110)$, namely, $c(\mathbf{z}) = 6$.
- The ZM (cross parsing) algorithm, a variant of the LZ parsing algorithm, is a sequential parsing of a sequence $\mathbf{z}$ with respect to another sequence $\mathbf{x}$ (cross parsing). Let $c(\mathbf{z}|\mathbf{x})$ denote the number of phrases in $\mathbf{z}$ with respect to $\mathbf{x}$. For example, let $\mathbf{z}$ be as above and $\mathbf{x} = (10010100110)$; then, parsing $\mathbf{z}$ with respect to $\mathbf{x}$ yields $(011, 110, 00110)$, that is $c(\mathbf{z}|\mathbf{x}) = 3$.

Roughly speaking, we can see $c(\mathbf{z})$ as a measure of the complexity of the sequence $\mathbf{z}$, while $c(\mathbf{z}|\mathbf{x})$, the code-length obtained when coding $\mathbf{z}$ using a model for $\mathbf{x}$ (cross parsing), can be seen as an estimate of the cross complexity [23]. It is expectable that the cross complexity is low when the two sequences are very similar; this is the key idea behind the use of ZM cross parsing in classification [21], which in this paper will be adopted for ECG-based personal identification and authentication.

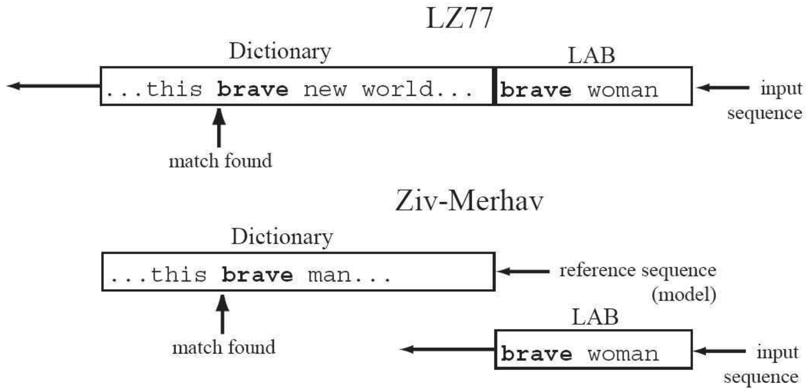

Fig. 2. The original LZ77 algorithm uses a sliding window over the input sequence to update the dictionary; in our implementation of ZM cross parsing algorithm, the dictionary is static and only the lookahead buffer (LAB) slides over the input sequence.

An implementation of the ZM cross parsing algorithm as a component of a ZM method for relative entropy estimation was proposed in [21], based on a modified LZ77 [17] algorithm, where the dictionary is static and only the lookahead buffer slides over the input sequence, as shown in Fig. 2 (for more details, see [21]). This very same implementation of the cross parsing, using a 64 Kbyte dictionary and a 256 byte look ahead buffer, was used in the experiments reported below.

3 Proposed Methods

To use ZM-based tools for identification or authentication, a necessary first step is the conversion of the ECG (discrete-time analog) signal into a sequence of symbols (text). In this paper, we propose a very simple approach based on quantization. Assuming we are given a set of single heartbeat waveforms (resulting from a segmentation preprocessing stage), we simply apply 8-bit (256 levels) uniform quantization, thus obtaining a sequence of symbols (from a 256 symbols alphabet) from each single heartbeat.

Quantizers with fewer bits were considered in early experiments but discarded because they didn't perform as well as the 8-bit quantizer. Higher values were not considered for sake of system implementation simplicity and because of the good performance obtained with 8 bits.

Consider a collection of training samples partitioned into K classes (the set of subjects to be identified): $\mathcal{X} = \{\mathcal{X}_1, \mathcal{X}_2, ..., \mathcal{X}_K\}$. For each subject/class k, $\mathcal{X}_k$ contains n strings obtained from the same number of heartbeats using the quantization procedure described in the previous paragraph. A string $\mathbf{x}_k$ is formed by concatenating the n training strings of subject k; string $\mathbf{x}_k$ is, in some sense, a "model" representing the shape of the heartbeats of subject k.

3.1 Identification

Given a test sample $\mathbf{z}$ (containing the string representing m heartbeats) obtained from an unknown subject (assumed to be one from which the training set was obtained), its identity is estimated as follows:

$$\hat{k}(\mathbf{z}) = \arg \min_{k \in \{1,\ldots,K\}} c(\mathbf{z}|\mathbf{x}_k),$$

where $c(\mathbf{z}|\mathbf{x}_k)$ is computed by the ZM cross parsing (ZMCP) algorithm, as described in Section 2. In other words, the test sample is classified as belonging to the subject that leads to its shortest description. Although using different tools, this approach is related in spirit with the *minimum incremental coding length* (MICL) approach [24].

3.2 Authentication

The authentication (verification) procedure depends on a threshold level, which depends itself from the range of values of $c(\mathbf{z}|\mathbf{x}_k)$. In order to limit its variation to a predefined set of values, normalization is used. Since in the worst case the description length, resulting from the ZMCP algorithm for the test sample $\mathbf{z}$, is the length of $\mathbf{z}$, the normalized description length $c_n(\mathbf{z}|\mathbf{x}_k)$ is defined as follows:

$$c_n(\mathbf{z}|\mathbf{x}_k) = \frac{c(\mathbf{z}|\mathbf{x}_k)}{len(\mathbf{z})},$$

where $len(\mathbf{z})$ is the number of bytes in test sample $\mathbf{z}$. Notice that $c_n(\mathbf{z}|\mathbf{x}_k) \in [0, 1]$. Test sample verification is made by comparing the value of $c_n(\mathbf{z}|\mathbf{x}_k)$ when using the claimed identity model with a threshold value $\in [0, 1]$, previously set according to a selected error rate, false acceptance rate (FAR), or false rejection rate (FRR). It decides for genuine when the comparison result is less or equal to the selected threshold level.

4 Experiments

The architecture of the proposed ECG-based biometric system for person identification and authentication follows the same model proposed by Jain et al in [1]. Fig. 3 shows the block diagram of the implemented system for the authentication task.

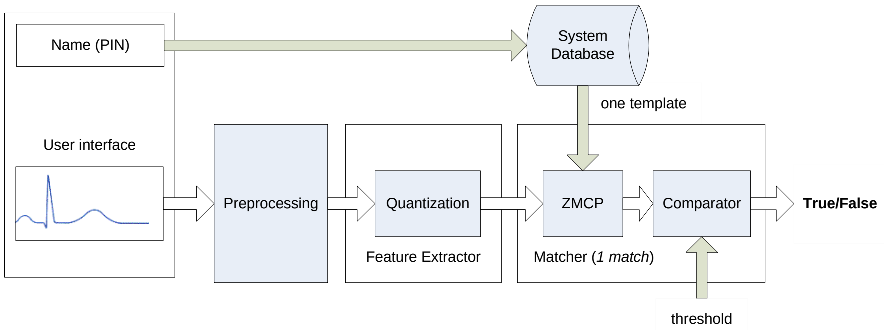

Fig. 3. Block diagram of the implemented system, for the authentication task, is shown using the five main modules of a biometric system, i.e., sensor, preprocessing, feature extraction, matcher and system database.

4.1 Data Collection

The ECG waveform dataset used was acquired using one lead, in the context of the Himotion project.[4] The dataset contains ECG recordings from 19 subjects acquired during a concentration task on a computer, designed for an average completion time of 10 minutes. All the acquired ECG signals were normalized and band-pass filtered (2–30Hz) in order to remove noise. Each heartbeat waveform was sequentially segmented from the full recording and then all the obtained waveforms were aligned by their R peaks. From the resulting collection of ECG heartbeat waveforms, the mean wave for groups of 10 consecutive waveforms (without overlap) was computed. Each of these mean waveforms is what we call a single heartbeat in Section 3.

An intra-class study [2] with the dataset, in the context of the exploration of electrophysiological signals for emotional states detection, showed the existence of differentiated states in the data that represent the ECG signal of a subject. To deal with this intra-class differences the proposed method includes in the "model" (as mentioned in Section 3) single heartbeats randomly selected from the whole ECG signal sample.

The reported results are averages over 50 runs. In each run, we partition the set of heartbeats of each subject into two mutually exclusive subsets: one of these subsets is used to form the training data set $\mathcal{X} = \{\mathcal{X}_1, \mathcal{X}_2, ..., \mathcal{X}_K\}$, while the other is used to build the test waveforms. We consider several values for n (the length of the "model" strings) as well as for m (the length of the test waveforms).

4.2 Identification Results

The results for the identification experiment, which are depicted in Fig. 4, show that the proposed method achieves 100% accuracy for $m = 12$ and $n = 13$ or $n = 20$. This is better than the results reported in [11] over the same dataset. The approaches in [8], [9], [13], were not tested on the same dataset, so the results are not directly comparable. Notice that using only $m = 5$ waveforms for the test patterns, we already reach an accuracy around 99.5%. As expected, the accuracy increases both with n and m.

[4] https://www.it.pt/auto_temp_web_page_preview.asp?id=305

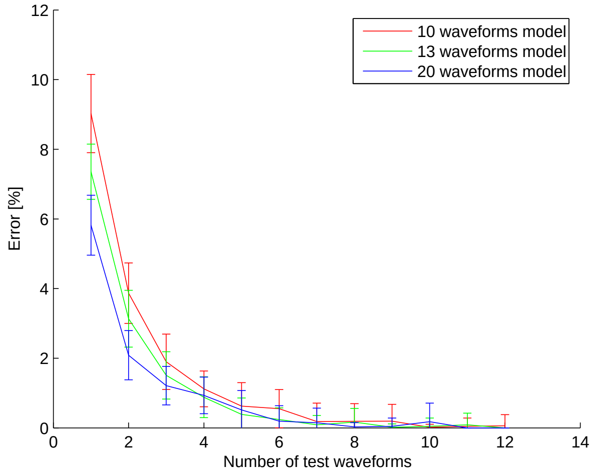

Fig. 4. Mean recognition error and standard deviation intervals for subject identification when considering a variable number of waveforms as test samples.

4.3 Authentication Results

Regarding verification (authentication) three different test were made. The first test follows the model shown in Fig. 3. The results, which are depicted in Fig. 5 (a), show that the proposed method achieves an overall equal error rate EER $\approx 6\%$. Notice that one can lower the error rate using lower threshold values but then the system will reject more legitmate users. However, it is possible to use lower threshold values if we use a different value for each subject (user-tuned thresholds).

The second test also follows the model shown in Fig. 3 but now the threshold is user-tuned. An equal error rate (EER) was computed for each subject and then an average EER is reported. The test results presented in Table 1 show that the proposed method outperforms fiducial approaches results reported in [25] and [26], over the same dataset.

Table 1. Comparison of verification related work results with our method, over the same dataset.

Reference	Feature	EER
Oliveira and Fred [26]	Fiducial (1-NN classifier)	8.0 %
Gamboa [25]	Fiducial (user tuned)	1.7 %
Proposed method	Non-fiducial (user tuned)	1.1 %

On the last verification test, we evaluate the combination of multiple source acquisition signals, classified by a bank of classifiers with the same structure of the first test, shown in Fig. 3, and a final decision made according to the majority voting criterion. Given a test sample (of length $m = 12$), it was decomposed in 64 different ways into samples of length $m = 6$ which were classified by a bank of 64 classifiers using the same threshold level and the same database. The results in Fig. 5 (b) show that this multiple classifier strategy doesn't improve the performance.

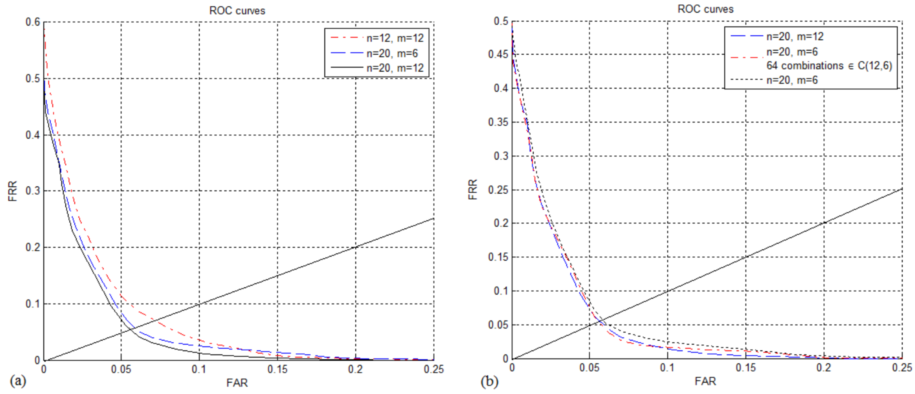

Fig. 5. ROC curves for the verification task (the solid straight line has slope 1, for reference purposes). Left plot: results for different n and m values; notice the improvement with the increase of m and n. The best equal error rate (EER) is close to 6%. Right plot: results for single classifiers versus a bank of 64 classifiers with the same structure for combination of multiple source acquisition signals.

5 Summary and Conclusions

We have presented a method for personal identification and authentication from one-lead ECG signals which involves no explicit feature extraction other than 8 bit uniform quantization of the waveforms. The classifier is based on the Ziv-Merhav cross parsing (ZMCP) algorithm, which is an estimator of the algorithmic cross-complexity [23], used to measure the similarity between the model waveforms and the test waveforms. Experiments carried out on a dataset with 19 healthy subjects, for whom the existence of differentiated states in the ECG data of a subject has been shown [2], showed that our method achieves 100% accuracy in recognition (identification) and an average equal error rate close to 1.1% in verification (authentication) tasks. Although further experiments, on other datasets, are needed to assess the relative performance of the proposed method, with respect to other state-of-the-art techniques, these results demonstrated the validity of our approach as a tool for personal identification and authentication, and of the ECG signal as a viable biometric. Future work will include tests with the Max-Lloyd quantizer and further evaluation of our method when used in an adaptive way for authentication purposes with continuous biometrics systems [7].

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References

1. Jain, A.K., Ross, A., Prabhakar, S.: An introduction to biometric recognition. IEEE Trans. Circuits Syst. Video Techn. 14 (2004) 4–20
2. Medina, L.A.S., Fred, A.L.N.: Genetic algorithm for clustering temporal data - application to the detection of stress from ecg signals. In: Proc 2nd International Conference on Agents and Artificial Intelligence (ICAART). (2010) 135–142
3. Ross, A.A., Nandakumar, K., Jain, A.K.: Handbook of Multibiometrics (International Series on Biometrics). Springer-Verlag New York, Inc., Secaucus, NJ, USA (2006)
4. N. V. Boulgouris (Editor), Konstantinos N. Plataniotis (Editor), E.M.T.E.: Biometrics: Theory, Methods, and Applications. Wiley-IEEE Press (2009)
5. Cunha, J., Cunha, B., Xavier, W., Ferreira, N., Pereira, A.: Vital-jacket: A wearable wireless vital signs monitor for patients mobility. In: Proceedings of the Avantex Symposium. (2007)
6. Leonov, V.: Wireless body-powered electrocardiography shirt. In: Proceedings of the Smart Systems Integration European Conference. (2009)
7. Damousis, I.G., Tzovaras, D., Bekiaris, E.: Unobtrusive multimodal biometric authentication: the humabio project concept. EURASIP J. Adv. Signal Process 2008 (2008) 1–11
8. Biel, L., Pettersson, O., Philipson, L., Wide, P.: ECG analysis – a new approach in human identification. IEEE Transactions on Instrumentation and Measurement 50 (2001) 808–812
9. Shen, T., Tompkins, W.J., Hu, Y.H.: One-lead ECG for identity verification. Proc. of the 2nd Joint Conf. of the IEEE Eng. in Medicine and Biology Soc. and the 24th Annual Conf. and the Annual Fall Meeting of the Biomedical Eng. Soc. (EMBS/BMES '02) 1 (October 2002) 62–63
10. Israel, S.A., Irvine, J.M., Cheng, A., Wiederhold, M.D., Wiederhold, B.K.: ECG to identify individuals. Pattern Recognition 38 (2005) 133–142
11. Silva, H., Gamboa, H., Fred, A.: One lead ECG based personal identification with feature subspace ensembles. In: MLDM '07: Proceedings of the 5th international conference on Machine Learning and Data Mining in Pattern Recognition, Berlin, Heidelberg, Springer-Verlag (2007) 770–783
12. Chan, A., Hamdy, M., Badre, A., Badee, V.: Wavelet distance measure for person identification using electrocardiograms. Instrumentation and Measurement, IEEE Transactions on 57 (2008) 248–253
13. Chiu, C.C., Chuang, C.M., Hsu, C.Y.: A novel personal identity verification approach using a discrete wavelet transform of the ECG signal. In: MUE '08: Proceedings of the 2008 International Conference on Multimedia and Ubiquitous Engineering, Washington, DC, USA, IEEE Computer Society (2008) 201–206
14. Wang, Y., Agrafioti, F., Hatzinakos, D., Plataniotis, K.N.: Analysis of human electrocardiogram for biometric recognition. EURASIP J. Adv. Signal Process 2008 (2008) 19
15. So, H., K.L.Chan: Development of qrs detection method for real-time ambulatory cardiac monitor. IEEE Engineering in Medicine and Biology Society. (1997) 289–292
16. Laguna, P., Mark, R., Goldberg, A., Moody, G.: A database for evaluation of algorithms for measurement of qt and other waveform intervals in the ECG. In: Computers in Cardiology 1997. (1997) 673–676
17. Ziv, J., Lempel, A.: A universal algorithm for sequential data compression. IEEE Transactions on Information Theory 23 (1977) 337–343
18. Ziv, J., Lempel, A.: Compression of individual sequences via variable-rate coding. IEEE Transactions on Information Theory 24 (1978) 530–536
19. Nelson, M., Gailly, J.: The Data Compression Book. M&T Books, New York (1995)
20. Salomon, D.: Data Compression. The complete reference. 3rd edition edn. Springer, New York (2004)

21. Pereira Coutinho, D., Figueiredo, M.: Information theoretic text classification using the Ziv-Merhav method. 2nd Iberian Conference on Pattern Recognition and Image Analysis – IbPRIA'2005 (2005)
22. Ziv, J., Merhav, N.: A measure of relative entropy between individual sequences with application to universal classification. IEEE Transactions on Information Theory 39 (1993) 1270–1279
23. Cerra, D., Datcu, M.: Algorithmic cross-complexity and relative complexity. In: DCC '09: Proceedings of the 2009 Data Compression Conference, Washington, DC, USA, IEEE Computer Society (2009) 342–351
24. Wright, J., Ma, Y., Tao, Y., Lin, Z., Shum, H.: Classification via minimum incremental coding length. SIAM Journal on Imaging Sciences 2 (2009) 367–395
25. Gamboa, H.: Multi-Modal Behavioral Biometrics Based on HCI and Electrophysiology. PhD thesis, Instituto Superior Técnico, Universidade Técnica de Lisboa, Lisboa, Portugal (2008)
26. Oliveira, C., Fred, A.L.N.: ECG-based authentication: Bayesian vs. nearest neighbour classifiers. In: Proc International Conf. on Bio-inspired Systems and Signal Processing - Biosignals - INSTICC, Porto, Portugal (2009)