ECG Biometrics: A template selection approach

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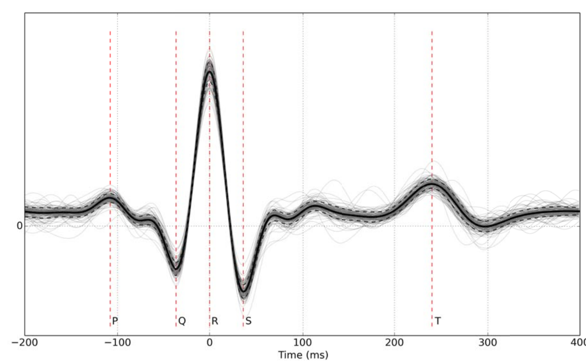
***Abstract*—Electrocardiography (ECG) biometrics is emerging as a viable biometric trait. Recent developments at the sensor level have shown the feasibility of performing signal acquisition at the fingers and hand palms, using one-lead sensor technology and dry electrodes. These new locations lead to ECG signals with lower signal to noise ratio and more prone to noise artifacts; the heart rate variability is another of the major challenges of this biometric trait. In this paper we propose a novel approach to ECG biometrics, with the purpose of reducing the computational complexity and increasing the robustness of the recognition process enabling the fusion of information across sessions. Our approach is based on clustering, grouping individual heartbeats based on their morphology. We study several methods to perform automatic template selection and account for variations observed in a person's biometric data. This approach allows the identification of different template groupings, taking into account the heart rate variability, and the removal of outliers due to noise artifacts. Experimental evaluation on real world data demonstrates the advantages of our approach.**

I. Introduction

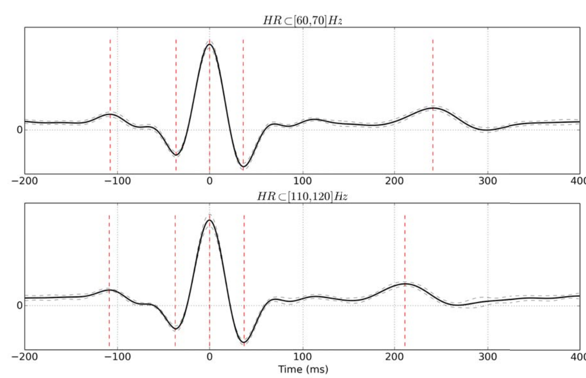
The biometric potential of the Electrocardiographic (ECG) signals has been shown at the beginning of the century [1], [2]. Traditionally, this signal was only used for clinical applications, but due to its specificities, the ECG is emerging as a particularly interesting biometric trait in multi-biometrics scenarios [3], as it is: a) Originated in the body by a vital organ, ensuring aliveness detection; b) Permanently available, providing a continuous and near-ubiquitous means of recognition; and c) More difficult to mimic, since there is no association with reproducible external landmarks, thus preventing fraud by means of artificial replicas.

The acceptance of ECG-based methods requires practical identity recognition scenarios, especially in what concerns the sensor devices, which has led to research on new ways of acquiring the ECG signal, with usability in mind [3], [4], [5]. 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, under an "on-the-subject" perspective as defined by [6]. State-of-the-art work enables ECG acquisition at the hand palms or fingers, on an "off-the-subject" approach, using one-lead sensor technology, 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. Experimental results have shown that this approach provides an adequate signal quality and biometric performance, even when compared with a more traditional chest setup [4], [5], [7], [8].

One of the current challenges of this biometric trait is the ability to deal with its intrinsic variability. As with other biometrics, each sample of the ECG biometric trait is slightly different, introducing intra-class variability [9]. In ECG biometrics the main sources of variability are [10]: a) Artifacts induced by the acquisition setup, such as power-line noise and low frequency motion-induced baseline wander; b) Heart rate changes, which lead to a compression or expansion of the heartbeat waveform; c) Aging, which leads to physical morphological changes that induce a variation on the heartbeat waveform; and d) Clinical conditions, since if any cardiac event occurs, the shape of the heartbeat waveform may suffer major variations.



(a) Segmented heartbeat waveforms



(b) Morphological changes

Fig. 1. Example of ECG signals acquired at the fingers: a) Segmented heartbeat waveforms with annotated complexes (P-QRS-T); the black line represents the mean, and the dashed lines the standard deviation, while in dark gray we provide an overlay with all the segmented heartbeats; b) Example of morphological changes to the heartbeat waveform caused by different heart rates. On the top figure the heart rate was in the interval $[60, 70]$ bpm, while on the bottom figure the heart rate was in the interval $[110, 120]$ bpm.

In Fig.1 we present examples of ECGs acquired on the

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fingers. Fig.1(a) shows the variability, visible with the naked eye, within a recording session, during which the acquisition was performed with the subject at rest in a still position. Fig.1(b) presents the morphological changes that can occur over different heart rates across multiple sessions, showing a visible change in the T complex. We superimpose the annotated complexes (P-QRS-T) for easier interpretation.

One way of integrating ECG-based biometrics into consumer devices is through autonomous embedded devices. Notwithstanding the enormous evolution these systems have seen over the last few years, constraints still exist regarding the memory footprint and processing throughput they are capable of handling, especially when developing miniaturized devices. Consequently, it is necessary to minimize the amount of information that is stored on the system.

In this paper we present a novel ECG-based biometrics approach designed around template selection. Our method enables automatic discovery of the templates that best represent a subject across sessions, leading to a more efficient system in terms of memory usage per subject. Our approach is based on clustering, grouping individual heartbeats based on their morphological similarity. It enables the capture of intraclass variability, for instance related with different heart rates.

The remainder of the paper is organized as follows: Section II provides an overview of ECG-based biometric systems and introduces the proposed approach; Section III presents our proposed template selection methodology and provides a framework for fusion of information across sessions; Section IV presents the experimental evaluation and main results; and finally, Section V outlines the main findings and overall conclusions.

II. ECG Biometric Systems

Within ECG-based biometrics, current methods can be classified as either fiducial or non-fiducial [3], [11], [12]. The former describes approaches based on reference points in the signals and/or specific features derived from them (such as the P-QRS-T complexes illustrated in Fig.1(a)) [13], [14], [15], [16]. The latter generally refers to techniques that rely on intrinsic information from the ECG signals, without having any particular cues within the signal as a reference [17], [18], [19], [20]. Partially fiducial, or combination, methods have also started to appear, where fiducial information is only used for ECG segmentation [4], [8], [20], [21]. We refer the reader to [3], [11], [12] for a comprehensive literature revision.

Our work follows a partially-fiducial framework, and in Fig.2 we depict the block diagram of the proposed biometric system. Raw data is acquired through a one-lead ECG sensor at the hands [7], and submitted to a preprocessing block that filters the signal. Afterwards, the outlier detection block uses all the available information for the detection and removal of anomalous ECG heartbeats. We follow the approach proposed in [22], where a distance-based criterion, entitled DMEAN is devised. DMEAN computes the distance from all templates to a single reference (the mean template for the recording session), and templates are considered as outliers if the distance is higher than an adaptive threshold and other empirical rules.

A pattern extraction block takes the preprocessed input signals, segments the signal into individual heartbeat waveforms [23], and computes a mean template from 5 consecutive heartbeat waveforms (creating a smoothed version of the template) [24].

During the enrollment stage, the system will extract heartbeat waveforms through the template selection block, which will then be used as representative templates for a given user on the recognition phase. In the classification stage, we use a multi-class support vector machine (SVM) classifier, with a *one vs one* approach, following the approach proposed in [5].

In the context of ECG-based biometrics, there are very few research papers focused on the fusion of information across multiple acquisition sessions. In [25] the proposed generative model can be used in an across-session scenario; the model can be re-trained using the features from both sessions. In this paper we propose an alternative methodology which is also tailored for across-session template extraction.

III. Template Selection

Let $X = \{x_1, \ldots, x_n\}$ be a set of n individual heartbeat waveforms, x_i, which can be described by a feature space of dimension m, $x_i = (x_i(1), \ldots, x_i(m)) \in \mathbb{R}^m$. Within the scope of our work, we consider the features to be the sample amplitudes of a heartbeat waveform comprised between the interval $[t_R - 200; t_R + 400]\, ms$, t_R being the time instant of the $R-$peak reference complex (see Fig.1(a)). Assuming a sampling frequency of $1000\, Hz$, this leads to $m = 600$.

The problem of template selection may be posed as follows: given a set of n heartbeats, select K templates that "best" represent the variability as well as the typically observed patterns according to a given similarity criterion.

Clustering methods are especially adequate for this task, and have already been used for template selection in other modalities [9], [26], [27], [28]. Let each clustering be represented as $\mathcal{P} = \{\mathcal{C}_1, \ldots, \mathcal{C}_K\}$, where $\mathcal{C}_j$ represents cluster j, and $d(\mathcal{C}_i, \mathcal{C}_j)$ the distance between clusters $\mathcal{C}_i$ and $\mathcal{C}_j$ according to a specified measure. Templates are usually selected from clusters determined from the instances representing each subject.

Uludag *et al.* [9] is one of the main contributions for the area of template selection in the context of fingerprint recognition, proposing two algorithms:

- **Dend**, which uses hierarchical agglomerative complete link (CL) algorithm [29] to group the instances into K clusters (fixed *a priori*). Then for each cluster, a prototype is chosen selecting the instance whose average distance to the other elements within the cluster is minimum.
- **Mdist**, which sorts all the samples based on their average pairwise distance, and selects those corresponding to the K smallest average distance.

A. Proposed Approach

In the context of ECG biometrics, and to our knowledge, no studies have been developed to date targeting template selection. Our approach is to tackle the problem based on Uludag *et al.* [9] and try different variants of their methodology. Their approach uses hierarchical agglomerative algorithms [29]. These algorithms build a binary tree that successively

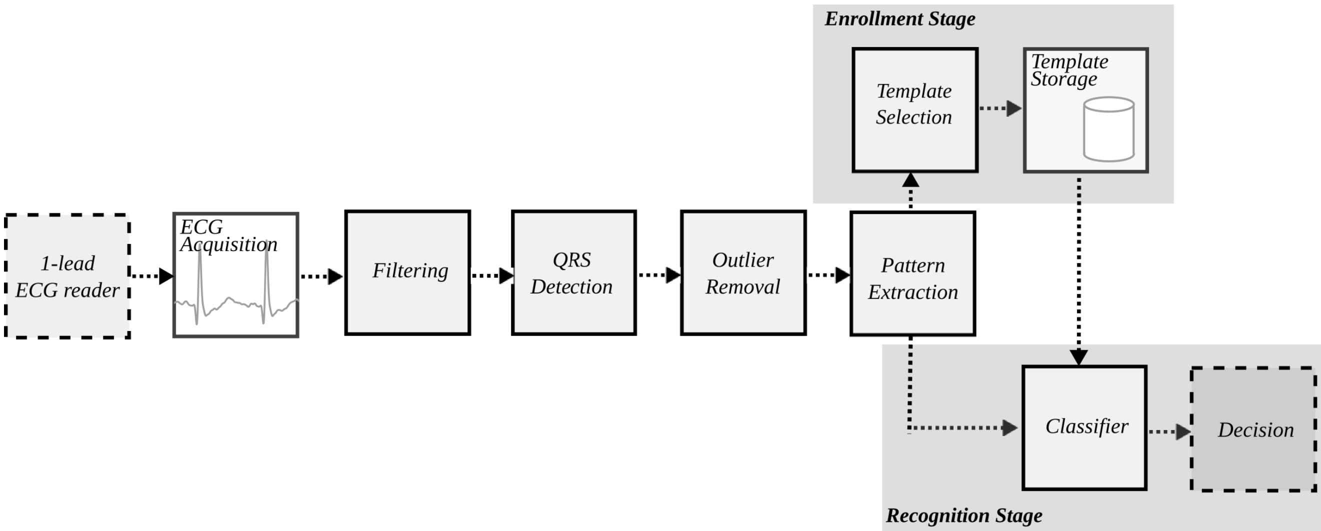

Fig. 2. Block diagram of the proposed ECG-based biometric system.

merges similar groups of points based on a linkage criterion. Given a distance metric between points, the linkage criteria allows us to choose how to define intergroup similarity, $d(C_i, C_j)$. In this work we used the following criteria:

- Complete Linkage (CL):

$$d(C_i, C_j) = \max\{D(a, b) : a \in C_i, b \in C_j\}$$

- Mean or Average Link (AL):

$$d(C_i, C_j) = \frac{1}{|C_i||C_j|} \sum_{a \in C_i} \sum_{b \in C_j} D(a, b)$$

These methods only require a measure of dissimilarity between instances $D(x_i, x_j)$. In this study we use as metric the Euclidean distance:

$$D_{eucl}(x_i, x_j) = \sqrt{\sum_{k=1}^{m} (x_i[k] - x_j[k])^2}. \quad (1)$$

For the template selection itself, we combine **Dend** and **Mdist** algorithms into a single method (**Mdist***), which selects a specified number K of templates, either from the complete set of the input templates, or from a partition $\mathcal{P}$, obtained with an arbitrary clustering algorithm, of that set:

- **Mdist*** without clustering – following the original **Mdist** algorithm, we select, as representative templates of the input set, the K samples with the smallest average pairwise distance;
- **Mdist*** with clustering – for each cluster, we select, as representative templates of the cluster, the K samples belonging to that cluster, which have the smallest average pairwise distance; this corresponds to applying **Mdist*** without clustering to each individual cluster; the **Dend** algorithm is a particular case of this approach, considering CL as the clustering method.

Unless otherwise stated, for the remainder of the paper, we refer to our **Mdist*** method simply as **Mdist**.

We also test another template selection methodology, denoted as **Centroids**, selecting as templates the centroids of the clusters. To produce the specified number of K templates per cluster, k-means is used to further partition the data in each cluster, with $k = K$. Note that all these approaches require the manual specification of the number of templates.

B. *Fusion Across Session*

Very few methodologies proposed in the literature provide a framework for taking into account the fusion of information across sessions [30]. Wan and Yau [31] use a neural network approach, in which inputs are concatenated feature vectors from different individuals, and from the same individual using more than a training session. Odinaka *et al.* [30] use a generative model of features derived from the frequency domain that has the ability to capture the variability across sessions.

We propose an across-session fusion process that consists on applying the **Mdist** or the **Centroids** algorithm over the multiple sessions. Our methodology automatically discovers templates that best represent a subject over different sessions, capturing the intra-class variability.

IV. Experimental Evaluation

A. *Performance Assessment*

In order the assess the performance of the system we focused on the authentication scenario. We computed, for each operating point (fraction of agreeing models in SVM), the False Acceptance Rate (FAR) and False Rejection Rate (FRR), given by

$$FAR = \frac{FP}{TN+FP}, \qquad FRR = \frac{FN}{TP+FN}, \quad (2)$$

where TP and TN are the number of true positives and negatives, and FP and FN are the number of false positives and negatives. From these rates, we estimate the Equal Error Rate (EER), which corresponds to the operating point for which the FAR is equal to the FRR, using piecewise polynomial interpolation.

B. Dataset

Following the recent trend towards off-the-person approaches [6], the ECG data acquisition was performed using a custom, one lead differential sensor design with virtual ground, found in [7]; for improved comfort, two dry Ag/AgCl electrodes were fitted to a supporting base, allowing the data to be acquired at the fingers. The sensor was connected to a bioPLUX research Bluetooth wireless biosignal acquisition unit. The signal was acquired using a 12-bit resolution, and $1\,kHz$ of sampling frequency.

A total of 63 subjects were enrolled in the experiment, which included two acquisition sessions separated by a 3-month interval. We denote the first acquisition session as *T1*, and the second as *T2*. The sample population is comprised of 14 males and 49 females, with ages ranging between 18 and 50 years (20.68 ± 2.83). None of the participants reported health problems, reason for which we consider the collected data to be representative of the normal population. All of the participants signed an informed consent form in order to participate in the experiment. In each of the sessions, the subjects were asked to sit for 2 minutes in a resting position, with one finger from the left hand and another from the right, placed in each of the dry electrodes.

For signal processing, we used the Python language, together with the standard modules for scientific computing, and the scikit-learn [32] toolbox.

C. Experimental Setup

We used various configurations for the training and testing sets, aiming to test the differences between within- and across-sessions, particularly:

- Within-session analysis – training the classifiers with the selected templates extracted from session *T1*, and testing with data from the same session (*WS-T1*);
- Across-session analysis (without fusion) – training the classifiers with the selected templates extracted from session *T1*, and testing with data from session *T2* (*AS-T2*);
- Across-session analysis (with fusion) – training the classifiers with the selected templates extracted from session *T1* and *T2*, and testing with data from session *T2* (*ASF-T2*).

To increase the statistical significance of our analysis we performed several runs for each configuration:

- *WS-T1* – 10 runs; 30% of the samples of *T1* were used exclusively for extracting the templates; testing was performed on the samples of *T2* not used for training;
- *AS-T2* – 1 run; all the samples of *T1* are used of training; testing performed on *T2*;
- *ASF-T2* – 10 runs; *T1* and 30% of the samples of *T2* were used of training; testing was performed on the samples of *T2* not used for training.

We evaluate the performance of the methodology described in the previous sections, analyzing systematically each of the components: a) Clustering methods (CL and AL); and b) Template selection methods (Mdist with clustering, Mdist without clustering, and Centroids).

D. Results

For the analysis of the template selection method, we fixed the outlier detection method, choosing the DMEAN algorithm, since it was shown that it was the one with better performance [22]. We use the authentication scenario and compare the EER of the template selection methods as a function of the number of templates (5, 10, 15), and the clustering algorithm algorithm (AL, CL, or None) in the different configurations of training and testing sets: *WS* - within-session, Fig.3; *AS-T2* - across-session analysing (without fusion), Fig.4; *ASF-T2* - across-session analysis with fusion, Fig.5. In each figure the red line represents the baseline result, obtained using all the templates for training.

The centroid method consistently presents better results than the Mdist method, either using the AL or CL as clustering criterion, and than the Mdist without clustering (None column). The differences are more significant in the across-session analysis with fusion – *ASF*.

Regarding the performance as function of the number of templates, the performance of the Centroids-based algorithms is different from the Mdist. For the former, the performance is inversely proportional to the number of templates (decreasing as the number of templates increases), while in the latter case we have the opposite behavior (improving as the number of templates increases). We can conclude that even with 5 templates we obtain a good performance (not significantly different from the case of 15 templates).

Comparing the performance in the different configurations, the best overall results are obtained within-session, where in several situations the obtained EERs are better than the baseline situation. In the across-session analysis (without fusion) the Mdist and Centroids algorithms obtain a worse result than the baseline situation. This configuration is the most difficult since we are comparing patterns of two sessions (training in one, testing in the other). The result can be supported due to the fact that there is high variability in the testing set, and using less information in the training set leads to a worse performance.

Finally, in the across-session (with fusion) the Centroids method obtains results similar with those of the baseline method.

In Fig.6 we present examples of extracted templates with the Mdist with clustering (using CL as clustering criterion), superimposing the templates across sessions. The red lines indicate the extracted templates, while the green lines highlight the heartbeats used for testing. The extracted templates capture a difference in heart rate (evident on the T wave latency), showing that the proposed methodology helps in capturing all the variability introduced by data obtained from different sessions, leading to an improvement on the global across-session performance.

V. Conclusion

ECG-based biometrics has the potential to complement existing approaches, or in some contexts be used as a single modality due their intrinsic nature. As in other biometric traits, each sample of the ECG is slightly different, contributing to the intra-class variability. In this paper we summarize the

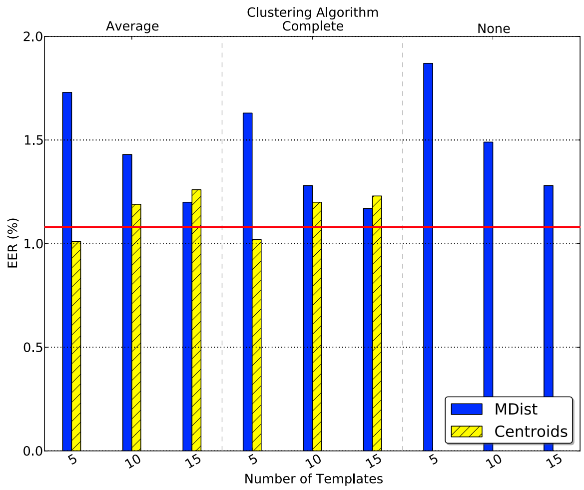

Fig. 3. Comparison of the performance (EER) - WS - within-session analysis; red horizontal line denotes the baseline method.

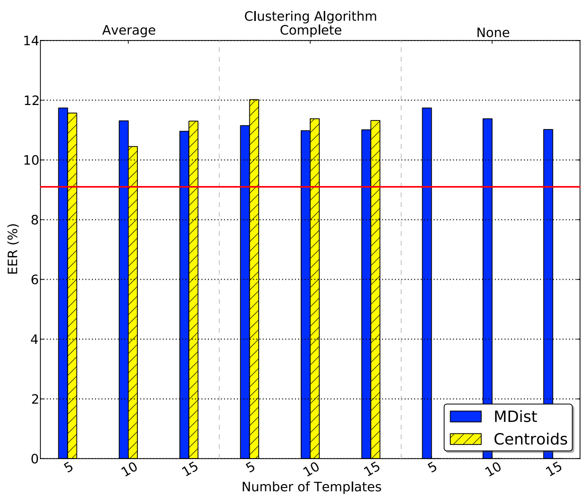

Fig. 4. Comparison of the performance (EER) AS-T2 - across-session analysis (without fusion); red horizontal line denotes the baseline method.

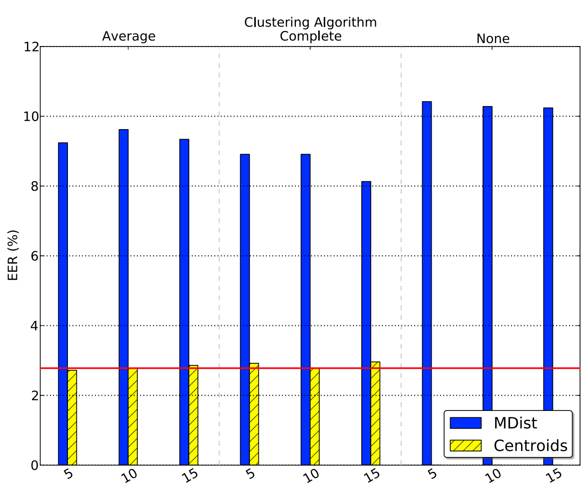

Fig. 5. Comparison of the performance (EER) - ASF-T2 - across-session analysis with fusion; red horizontal line denotes the baseline method.

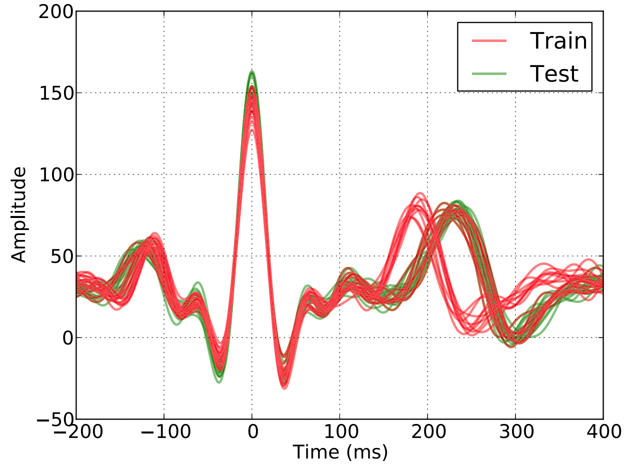

Fig. 6. Comparison between the training and testing templates for two example subjects; templates were selected with Mdist, using CL as clustering and extracting 5 templates per cluster; the red lines indicate the extracted templates, while the green lines the heartbeats used for testing.

main sources of such variability and present solutions aiming to reduce its effect. We present a novel approach relying on template extraction, based on clustering techniques, that enable the fusion of information across sessions and the decrease of the complexity of training the classifiers.

The presented system led to quite interesting results, both in terms of performance and computational complexity, showing potential for its integration on embedded devices. The best results for the across-session setup with fusion were obtained using the Centroids method, using AL as clustering and extracting 5 templates. Experimental results have shown that our approach enables high recognition rates, enhancing the state-of-the-art performance across sessions, and further validating ECG-based behavioral biometrics as a promising and interesting complement to other modalities.

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