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Client threshold prediction in biometric signature recognition by means of Multiple Linear Regression and its use for score normalization

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ABSTRACT

Biometric person authentication has become an important area of fieldwork both for research and commercial purposes in the last few years. The development of the technology, now ready for practical applications, has encouraged the scientific community to focus on practical issues. In this sense, a key question is the decision threshold estimation. Biometric authentication is a pattern recognition problem where a final decision (identity accepted/rejected) must be taken; so, to set a correct decision threshold is essential, since the best system becomes useless if an inaccurate decision threshold is fixed. This work focuses on this subject for biometric systems based on manuscript signatures. The decision threshold can be client (signatory) dependent or the same for all (common threshold). In this paper, new approaches for both problems are shown. A new solution, based on the Multiple Linear Regression model, is proposed for client dependent decision threshold estimation or prediction. The state of the art shows that only independent variables based on the Gaussian scores distribution supposition have been used. Here, new robust parameters, not based on that supposition, have been successfully included in the model. This proposal has been evaluated by means of both a statistical validation and a performance comparison with the state of the art. When a common threshold is used, the problem is to normalize the client scores. A new proposal for this task is also shown, based on the use of the predicted client threshold. Both proposals have been multi-working point, multi-corpus and multi-classifier tested. Improvements from 12% to 57% have been achieved with respect to the state of the art in threshold prediction, while these improvements are from 15% to 40% in the score normalization task.

1. Introduction

Over the last few years, our work has been concerned with biometric recognition with successful results [1–5]. These works approach technological aspects of the system, focusing on the feature extraction and recognition stages. However, the development of the recognition systems, now ready for practical applications, has encouraged us to go into the final decision stage in greater depth. This work focuses on this part, presenting new proposals related with the a priori client decision threshold estimation in biometric person authentication based on manuscript signature. This threshold estimation is essential for practical purposes.

Biometric recognition can be defined as the use of unique human characteristics (biometrics) to recognize the user (client or Target Class, TC). It can be split into two groups: *identification* (who is the owner of this biometric?) and *verification* or *authentication* (Am I the person I claim to be?). This second task is the one approached in this work.

Among the several biometrics used (e.g., iris, fingerprint, face or voice), manuscript signature (from here on "signature") presents some advantages [2], such as for example, that it is widely accepted and commonly used in legal and commercial transactions as an authentication method. Besides, there are no acquisition costs if a tactile device, as for example a smartphone, is used. For these reasons, it is the second most important [6] of the behavioral biometrics [7], i.e., those biometrics based on measurements and data derived from an action performed by the user.

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Signature recognition can be split into two categories: (i) *Static or off-line*, where the signature written on paper is digitized through an optical scanner or a camera, and (ii) *Dynamic or on-line*, where users write their signature in a digitizing device; the information acquired depends on the input device.

Taking into account the highest security levels which can be achieved by dynamic systems, most of the efforts of the international scientific community are focused on the latter group [8]. Static systems are restricted to use as an aid to identifying criminals in legal cases [9]. Our work is concerned with dynamic (online) signature recognition. Depending on the test conditions, two types of forgeries can be established: (i) *Skilled forgery*, where the impostor imitates the client signature, and (ii) *Random forgery*, where the impostor uses his/her own signature as a forgery.

Biometric authentication in general, and signature recognition in particular, is a pattern recognition problem where an input sample (signature) is classified into one of two categories (classes): Target (accepted, that is, the signature belongs to the user, i.e, it is authentic) and Non Target (rejected, which means that the signature does not belong to the user, i.e., it is a forgery). This final decision is performed by comparing the classifier score (output) with the client (user) threshold.

In development tasks, this decision threshold can be estimated a posteriori. However, in real applications, the client threshold must be established a priori, and it is fundamental to optimize the system performance. Several important problems arise concerning threshold accuracy estimation in real world biometric applications:

- It is common to have only a few data from the Target Class (client), biasing the statistics estimation [10].
- It is difficult, or even impossible, to get an adequate Non-Target Class, NTC, (impostors) representation in some biometrics. We can find some attempts in signature recognition focused on research tasks [11,12], but for practical applications, it is not legal to get forgeries in manuscript signatures.
- Generally, to simplify, the samples are supposed to be i.i.d. (independent and identically distributed), but in biometry this is not true; it is the so-called “biometric menagerie” [13].

In this work, a new approach to dealing with these problems in a priori client threshold prediction is shown. A preliminary work can be seen in [14], a more in depth study being presented here. Our proposal is based on the use of Multiple Linear Regression (MLR). Unlike other proposals, MLR is simple, easy to understand and to perform, since a lot of software tools can be found to work with this model. This proposal has been tested for multi-working points, i.e., it has been tested to predict thresholds for different, and representative, system performance points. In addition, a comparison with other prediction proposals in the literature has been performed, showing the advantages, in prediction accuracy, of our proposal. All of these tests have been performed with different corpora and with different signature verification state of the art systems. Dynamic Time Warping (DTW)-based systems have shown a very good performance in signature verification [5], while regarding the corpora, the MCYT database [15] is one of the most used, showing high, statistically significant results [16]. For these reasons, a more in depth study of our proposal has been performed with that classifier and that corpus.

In some practical applications (e.g., in the main independent biometric technology evaluations), instead of using a different threshold per client (TC), the same one is used for all the users (TCs), which means dealing with a different problem: given a learning paradigm, its Match (classifier outputs or scores for TC samples) and Non-Match (NTC scores) distributions vary depending on the classifier trained to distinguish one user from another (Fig. 1(a)). Thus, a scaling in Match and Non-Match distributions must be accomplished to bring the client distributions closer (Fig. 1(b)).

A very important research field nowadays in the use of multimodal biometrics, where several biometrics are combined to recognize the user, is to look for more robust systems. Under this approach, another source of score dissimilarity appears, since different matchers can be used for each biometric. For an adequate fusion, the matching scores of different matchers must be transformed into a common domain, that is, they must be normalized.

As can be seen, score normalization is an important, and sometimes critical, part of the biometric system. In this work, a new approach based on the a priori client estimated threshold is successfully proposed.

The rest of the paper is organized as follows. We begin, in Section 2, with the theoretical background of the problem approached. A brief analysis of the state of the art in a priori client threshold estimation and in score normalization can be seen in Sections 3 and 4, respectively. Our proposals for both problems are shown in Sections 5 and 6, respectively. After describing the experimental setup with the DTW-based sytem and the MCYT corpus (Section 7), the results achieved in a priori client threshold estimation can be seen in Section 8, and those achieved in score normalization are shown in Section 9. The results with other corpora and with another state of the art system can be seen in Section 10. All of these results sections include the corresponding comparative studies with the state of the art. The conclusions can be seen in Section 11.

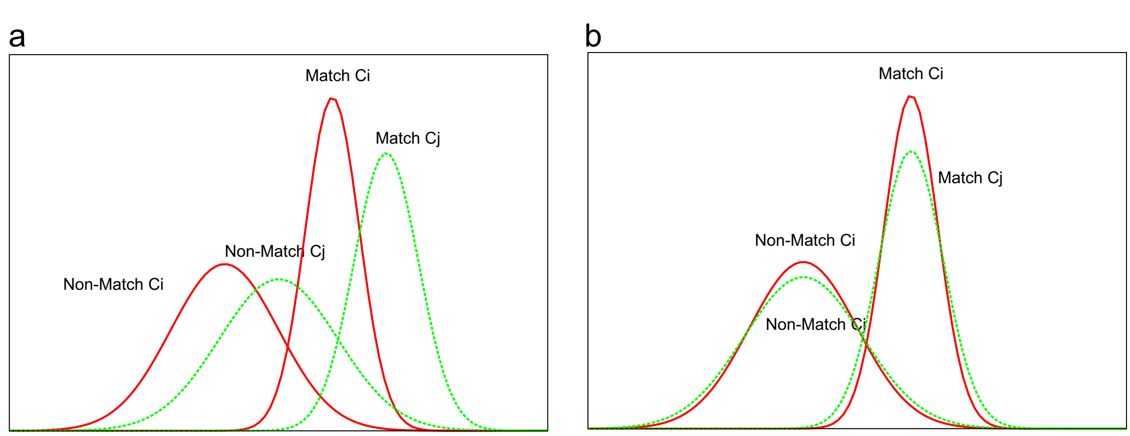

Fig. 1. Example of Match and Non-Match distributions of two users, (a) without score normalization and (b) with score normalization.