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WHY TEMPLATE SELF-UPDATE SHOULD WORK IN BIOMETRIC AUTHENTICATION SYSTEMS?

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ABSTRACT

The term *adaptive biometric systems* refers to biometric recognition systems in which an algorithm aimed to follow variations of the clients appearance has been implemented. Among others, the self update algorithm is used when only one biometric is available, and is able to add to the clients gallery novel data collected during system operation, on the basis of a updating threshold: if the novel data, compared with existing template(s), provide a matching score higher than the given threshold, they are added to the gallery. In order to avoid misclassification errors, thus inserting impostors into the clients gallery, this threshold is very conservative. Self-update algorithm has shown to be effective for many biometrics. However, no work tried to explain, so far, why self-update should work, in particular when a very conservative update threshold is used (zeroFAR threshold). This is the goal of the present paper, which provides a conceptual explanation of the self update mechanism coupled with a set of experiments on a publicly available data set explicitly designed for studying adaptive biometric systems.

1. INTRODUCTION

Biometric authentication systems [1] are aimed to substitute standard methods for personal recognition which use PIN and/or passwords. They are based on biometrics: physiological or behavioural traits that can be claimed as unique. Examples of biometric traits are fingerprint and face. When using biometrics for personal recognition, an individual, usually named user or client, needs to be ”enrolled” into the system. In other words, he/she submits the selected biometrics, which is captured as an image or as a signal. This data is processed and a set of features, characterizing the uniqueness of his/her trait, is extracted. This set represents the so-called ”template”, which is stored into the system database.

During system operation, the individual which wants to be authenticated, claims his identity and submits the selected biometric. A process similar to that of enrolment follows, but the set of extracted features is compared with the template of the claimed identity by a matcher, which implements a pairwise similarity function between the input sample and the template(s). The output is a matching score, usually a real value in the [0,1] interval. The score measures the level of similarity between an input sample and the clients template. If this score is higher than a certain acceptance threshold, the identity is authenticated and the individual is classified as a genuine user, otherwise he is classified as an impostor [1].

A biometric authentication system can be easily referred to a pattern recognition system based on template matching [2]. Consequently, it is tipically characterized by the False Acceptance Rate (FAR) and False Rejection Rate (FRR). The former is the percentage of impostors wrongly accepted, the latter is the percentage of genuine users wrongly rejected. The acceptance threshold t^* sets the operational point of the whole Receiver Operating Characteristic (ROC) curve which is given by FAR and FRR computed for each $t^* \in [0, 1]$.

A good ROC curve depends on several factors. Among others, the representativeness of the template(s) stored into the system database. Unfortunately, Refs. [3, 4, 5, 6] point out that it is impossible to store a template able to face with the intrinsic changes of the users biometrics in the short-medium time. In fact, a biometric can be subjected to temporary changes (a scratch on the fingertip or the face, appearance change due to illness for example) or temporal changes (biometric ageing).

On the other hand, the usual solution of performing additional enrolment sessions is very expensive and not necessarily effective due to the peculiar changes affecting biometrics. Therefore, several automatic updating algorithms have been proposed to this aim. Thus, an *adaptive biometric system* is a biometric authentication system empowered with an algorithm aimed to follow variations of the clients appearance.

These updating algorithms basically use the own knowledge of one or more biometric systems in order to automatically select the novel templates, which are added into the template set, named ”gallery”: template self-update algorithm [4, 7, 8, 9], graph-mincut algorithm [10] , co-update algorithm [11]. Among others, self-update is the most widely used, and is also the focus of this paper.

Briefly, self-update classifies the input samples as a possible template if the matching score with existing ones is above a updating threshold, considerably higher than the acceptance threshold, in order to assure that no impos-

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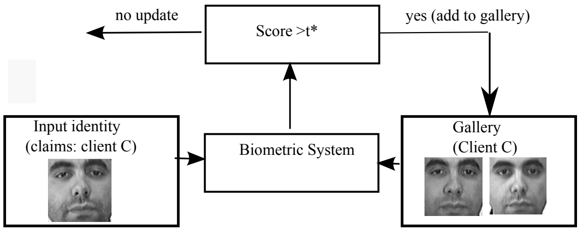

Fig. 1. Self-update flow diagram.

tors are considered as templates into the gallery. To this aim, the updating threshold is set to the so-called zeroFAR operational point, such that FAR=0%.

Although the state-of-the-art shows that template self-update works, sometimes pretty well, the literature lacks of any explanation about why template self-update should work, especially when a very conservative update threshold is used (zeroFAR). Therefore, the goal of this paper is to provide a first explanation, and to improve the understanding of factors that influence template self-update operation.

This paper is organized as follows. Section 2 provides a conceptual representation aimed to describe the functioning of the self-update algorithm. Section 3 describes some targeted experiments supporting the description in Section 2. Experiments are conducted on a publicly available data set explicitly conceived for studying adaptive biometric systems. Faces are used as a case-study for supporting the proposed conceptual representation. Section 4 discusses reported results and gives some preliminary conclusions.

2. CONCEPTUAL EXPLANATION OF TEMPLATE SELF-UPDATE OPERATION BASED ON PATH-BASED CLUSTERING

Self-update algorithm is basically very simple. During system operations, a person requires authentication by submitting his face to the system. This image is processed and a feature set is extracted and compared with existing templates. If the resulting match score is higher than the updating threshold, usually set to the zeroFAR operational point, the features set is classified as a novel template and added to the client's gallery. For the next access trials, the gallery with the added template will be used for authenticating people of the given client. The algorithm iterates until a certain stop criterion is met: for example, the system memory devoted to the template storing is full. At this point, other algorithms are needed to managing the gallery and the template updating [12], and are out of the scope of this paper. Fig. 1 summarizes the self-update algorithm as we described.

Self-update can be applied at each access trial (*online self-update*) or after that a certain time slot is passed and a certain amount of potential templates, named batch, has been reached (*offline self-update*) [11]. In this last case, that is, the one we investigated here, template update is performed after that biometric authentication system has been turned in the offline mode.

The starting point of the template self-update is the consistency of the gallery. We may consider, for example, the simplest case of one template per client. As an input sample is submitted, the related match score with respect to the existing template. If this score is higher than the updating threshold, the input sample is added to the client's gallery. We may represent this "connection" as an edge linking the template and the input sample, as in Fig. 2. When another input sample is submitted is enough that at least its match score with one of two available templates is above the threshold. Thus another edge can be eventually drawn, between the input sample and the "winner" template(s). As we can see, we are treating each sample as a node of a graph and a connection is drawn if and only if the matching score among two nodes is above the given threshold. Obviously, as the gallery size increases, if more than two templates exhibits a score above the threshold, an edge from each template to the input sample is drawn. The process described so far can be associated to the so-called *path-based clustering* [13].

A path-based cluster is defined as follows:

- let $f(x_i, x_j)$ be a pairwise similarity function on the samples (graph nodes) x_i, x_j;
- let t^* be a threshold value;
- x_i, x_j are connected by an edge if $f(x_i, x_j) > t^*$.

Thus, two patterns x_h, x_k, which are assigned to the same cluster, are either similar ($f(x_h, x_k) > t^*$), or a set of n intermediate patterns exists such that two consecutive patterns in this "chain" are similar: $f(x_h, x_{i,1}) > t^*$,..., $f(x_{i,n}, x_k) > t^*$.

According to this definition, there are nodes which cannot be connected, but form themselves one or more graphs, following the same rules. The starting templates can be viewed as the seeds of this clustering. They can be localized in the same graph, because a path among them exists, or to two ore more graphs (depending on their number). Therefore, only nodes (input samples) that follow the rules of path-based clustering can be reached from those seeds, whilst the others can't be reached.

From the biometric system point of view, this means that:

- there are input samples, representing variations, or changes, of the subject appearance, that cannot be exploited by self updating, since they are intrinsically out of the graphs drawn by the path-based clustering. These samples may represent *abrupt changes*[1] of the input data, including intrinsically *isolated* samples;
- on the other hand, there are data which do not form paths in the graph, because the *intermediate* sample(s) connecting them with existing templates (samples already added into the client's gallery) is (are)

[1] this term is often used in the pattern recognition field named *change detection*, often applied to video-surveillance problems [14].

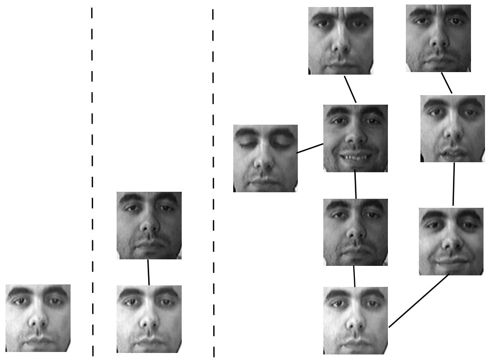

Fig. 2. Path drawing of two samples according to the path-based clustering rule.

not yet submitted to the system. The longer is the path required to connect initial template to these samples, the more these may represent some significant *temporal or temporary changes* of the subject appearance. They may be neglected by self-update until the required samples, or other samples alternatively connected, appear.

It is worth pointing out that this conceptual representation is merely geometrical, thus it does not take into account the probability of occurrence of a certain sample, that is, the probability of connecting two nodes of the path, which is out of the path-based clustering theory [13].

On the basis of the observations above this representation allows to draw the following claims, that will be supported by experiments reported in Section 3:

1. initial template selection is crucial for the self-update efficiency: if only one template is available, it should belong to a path-based cluster such that many samples may be potentially reached. If more templates are available, they should be located in different path-based clusters;

2. samples temporary neglected may anyway belong to one of existing path-based clusters, due to the temporary absence of intermediate samples or alternative paths;

3. the updating threshold may allow to draw those alternative paths, or completely novel paths, thus allowing also the "fusion" of two or more path-based clusters.

3. EXPERIMENTAL RESULTS

3.1. Data set

The DIEE multimodal data set has been specifically designed and collected in the PRA Group[2] laboratory for studying adaptive biometric systems. It contains 2,400 images from 40 clients, thus 60 images per client. These has been collected during ten different enrolment sessions over a time span of two years. Consequently, they exhibit significant differences in expressions, lighting and ageing of the individual, whilst the pose is always frontal. An example of these images has been reported in Fig. 3.

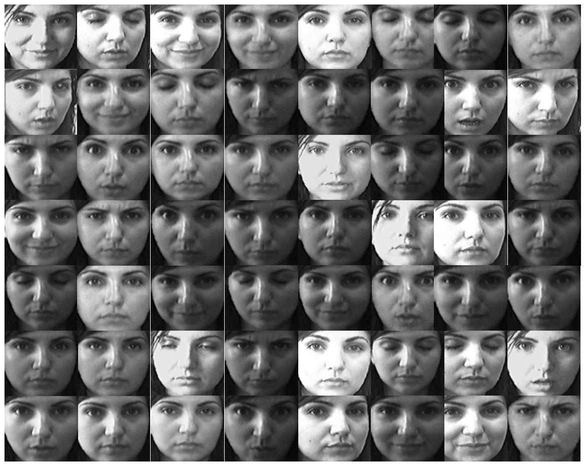

Fig. 3. Some example images from the DIEE multimodal data set.

Face images are originally coupled with fingerprint images[3], that have not been taken into account in this paper. The data set is downloadable by contacting the authors.

3.2. Results

All experiments have been performed on a face recognition system based on the matcher called Elastic Bunch Graph Matching [15]. In all cases, self-update has been run by starting from only one template per client.

In order to show the first claim of Section 2, we run self-update algorithm on each client of the DIEE multimodal data set. In this first set of experiments, the updating threshold has been set to the zeroFAR operational point. For sake of space, this paper only shows results related to two representative clients.

Fig. 4 and Fig. 5 show a subset of the path-based clusters when performing self updating on all images available. It is evident that these clients are characterized by

[2]Pattern Recognition and Applications Group (http://prag.diee.unica.it).

[3]This motivates the name of "multimodal" data set, that is, made up of more than one biometric modality, or trait.

very different clusters. In particular, Fig. 4 points out that client 1 is characterized by a path-based cluster whose size is much wider than that of other clusters. We have a *dominant* cluster. In this case, selection of the template allows the best performance if a sample of the dominant cluster is selected. This is impossible to know during the design setting, but it is also interesting to notice that, due to the presence of the dominant cluster, even patterns significantly "different" by visual inspection can be captured as well, so the template selection phase is not crucial.

Fig. 5 shows that other clients can be characterized by many path-based clusters. This means that the choice of the initial template can be crucial depending on the particular working environment of the system. In this case, it is evident that changes in terms of lighting conditions are not well tolerated (this happened even for other clients exhibiting similar characteristics), thus self-update, working at zeroFAR operational threshold, can't adapt the system with respect to these significant variations.

With regard to the second claim of Section 2, we may notice, in both cases, the presence of more than one clusters. We may also notice several isolated samples. But this topology is consequence of the selected threshold, thus it is possible that some of them have not been inserted because of: (1) the lack of the intermediate samples, (2) the too stringent threshold. Since all images of DIEE multimodal data set have been considered here, item (1) is not verifiable. On the other hand, we can easily verify item (2) by relaxing the updating threshold. This allows also to support the third claim of Section 2.

Fig. 6 and Fig. 7 show a subset of the path-based clusters of the same clients obtained by applying a updating threshold set to the 0.5%FAR operational point. It can be easily noticed that, in both cases, the number of clusters is reduced. This effect is particularly relevant by comparing Fig. 5 with Fig. 7, where several connections among samples appeared and caused the fusion of several clusters, as well as the connection of many isolated samples. The consequence of this is that the choice of the initial template becomes less crucial even for this kind of clients.

This is confirmed in Fig. 8 and Fig. 9. In these plots we reported in the x-axis the number of iterations performed by self-update algorithm, and, in the y-axis, the correspondent False Rejection Rate (FRR) obtained on the whole data set. The novel samples inserted into the client's gallery are not considered for the FRR computation at each iteration. Reported curves are averaged over 25 runs of the self-update algorithm by randomly extracting the initial template. It is possible to notice that, although the presence of individual path-based clusters in client 2 (Fig. 5), threshold relaxation allows the same amount of performance improvement pointed out in Fig. 8. Accordingly, the performance increases (Fig. 9), and this is explained by the novel paths (Fig. 7). Since $FAR \neq 0\%$, the performance increase is counterbalanced by the risk of adding impostors into the clients gallery [7, 10, 11].

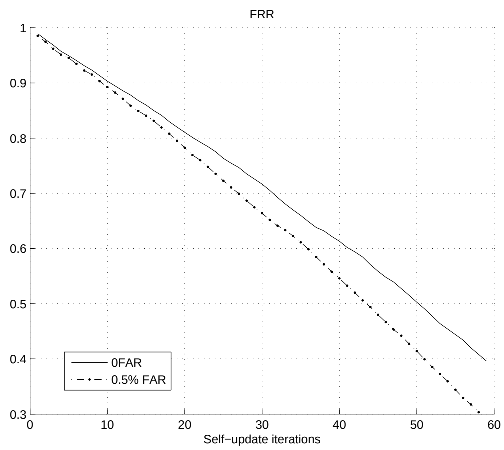

Fig. 8. In this plot, the False Rejection Rate (FRR) related to client 1 is shown as function of the iteration steps of self-update, using a zeroFAR updating threshold, and a relaxed threshold (0.5%FAR). It is easy to notice a performance increase by relaxing the threshold from zeroFAR to 0.5%FAR.

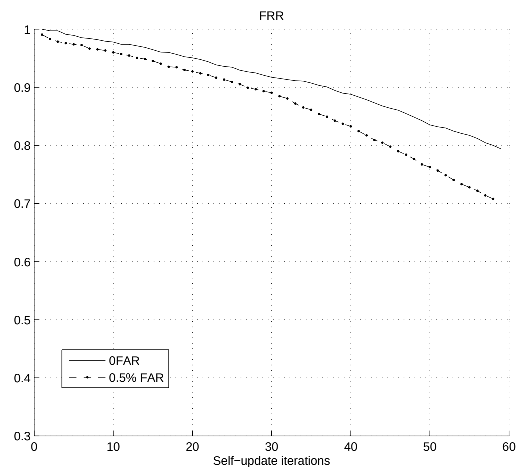

Fig. 9. In this plot, the False Rejection Rate (FRR) related to client 2 is shown as function of the iteration steps of self-update, using a zeroFAR updating threshold, and a relaxed threshold (0.5%FAR). Although the peculiar topology of the path-based clusters of client 2 (Fig. 5), a significant performance increase is noticed by relaxing the threshold from zeroFAR to 0.5%FAR, which allows drawing novel paths in order to capture more intra-class variations (Fig. 7).

4. CONCLUSIONS

In this paper, we proposed a conceptual view to explain the working mechanisms of the self-update algorithm. Self-update is the most widely adopted algorithm to template update in biometric authentication systems. Although several authors show that it may achieve a high level of performance, no research so far explains why this happens.

Using the path-based clustering view, we have been able to formulate several claims, which have been sup-

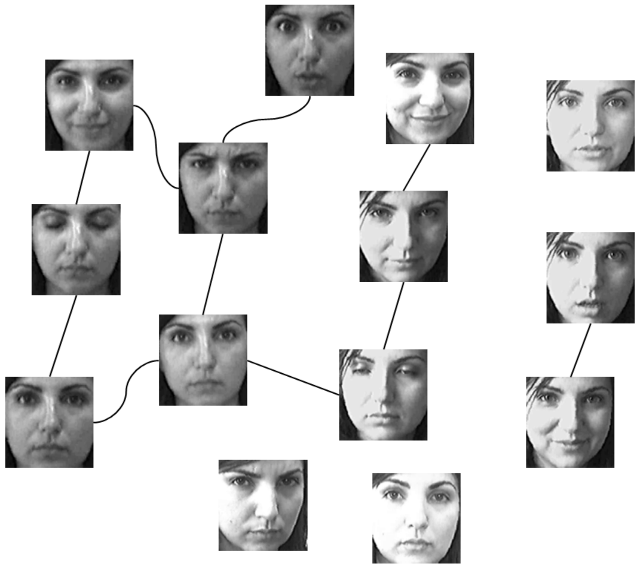

Fig. 4. Path-based clusters of the example client 1. A dominant cluster can be pointed out.

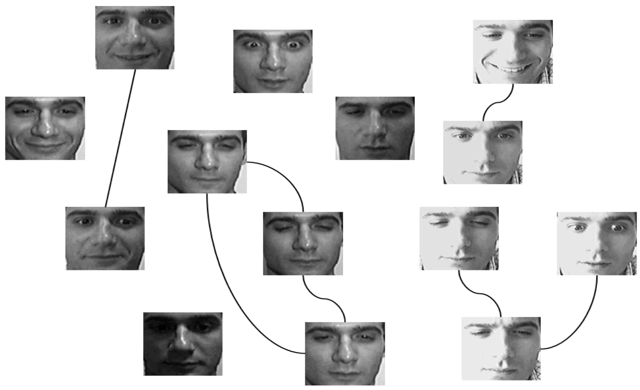

Fig. 5. Path-based clusters of the example client 2. No dominant clusters are pointed out.

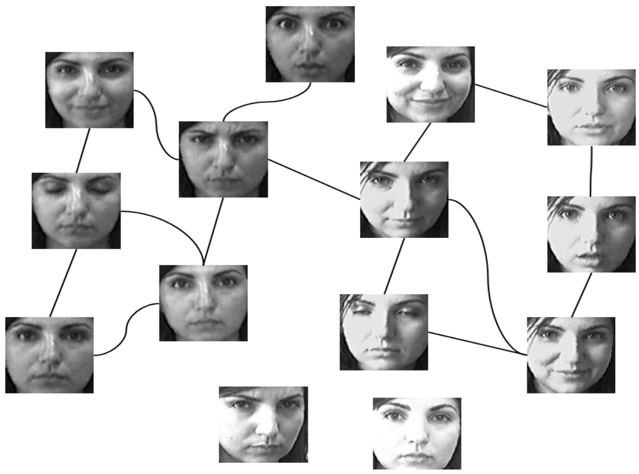

Fig. 6. Path-based clusters of the example client 1, where the updating threshold has been relaxed to the 0.5%FAR.

ported by a set of experiments carried out on a data set explicitly conceived for studying and designing adaptive biometric systems. In particular, we pointed out that: (a) the selection of initial templates may be crucial for certain clients; (b) neglected input samples may be recovered by running self updating steps at different time periods, when novel samples have been collected; (c) the threshold relaxation may allow to update successfully clients where the toleration to certain environmental variations (for example, lighting variations) is very low.

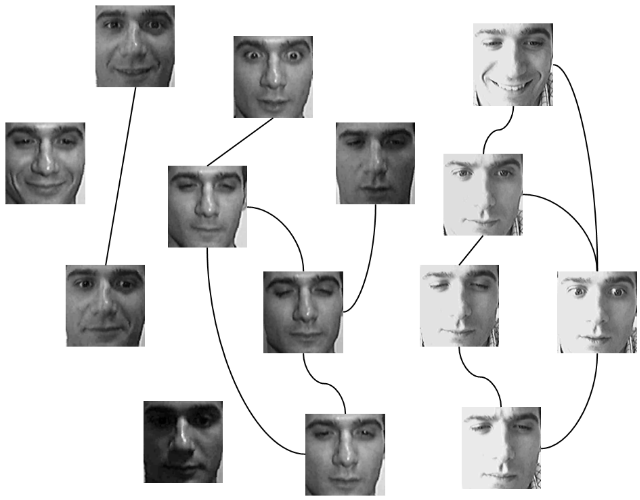

Fig. 7. Path-based clusters of the example client 2, where the updating threshold has been relaxed to the 0.5%FAR. Several clusters, separated in Fig. 5, have been merged, thus simplifying the problem of initial template selection.

Although it is not possible to draw definitive conclusions on the basis of this limited set of experiments, we believe that the path-based clustering suggested some interesting points of view in order to explain the behaviour of the self-update algorithm, thus it is worthy to be further investigated on other biometric traits and real-world data sets.

5. ACKNOWLEDGMENTS

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