# Frontal face authentication using variants of dynamic link matching based on mathematical morphology

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**Abstract**

*Two variants of dynamic link matching based on mathematical morphology are developed and tested for frontal face authentication, namely, the Morphological Dynamic Link Architecture and the Morphological Signal Decomposition - Dynamic Link Architecture. Local coefficients which weigh the contribution of each node in elastic graph matching according to its discriminatory power are derived. The performance of the proposed algorithms is evaluated in terms of their Receiver Operating Characteristic and the Equal Error Rate achieved in M2VTS database. The comparison with other frontal face authentication algorithms developed within M2VTS project indicates that Morphological Dynamic Link Architecture with discriminatory power coefficients is ranked as the best algorithm in terms of the Equal Error Rate.*

## 1 Introduction

Face recognition has exhibited a tremendous growth for more than two decades. A critical survey of the literature related to human and machine recognition is found in [1]. An approach that exploits both the grey-level information and the shape information is the so-called *Dynamic Link Architecture* (DLA) [2, 3, 4]. The algorithm is split in two phases, i.e., the training and the recall phase. In the training phase, the objective is to build a sparse grid for each person included in the reference set. Towards this goal a sparse grid is overlaid on the facial region of a person's digital image and the response of a set of 2D Gabor filters tuned to different orientations and scales is measured at the grid nodes. The responses of Gabor filters form a *feature vector* at each node. In the recall phase, the reference grid of each person is overlaid on the face image of a test person and is deformed so that a cost function is minimised.

In this paper, we develop variants of DLA that are based on mathematical morphology and incorporate local coefficients that weigh the contribution of each grid node according to its discriminatory power. We propose first a variant of DLA that is based on multiscale morphological dilation-erosion, the so-called *Morphological Dynamic Link Architecture* (MDLA). Another variant of DLA is based on morphological signal decomposition. It is called *Morphological Signal Decomposition-Dynamic Link Architecture* (MSD-DLA). Linear projections of the feature vectors at the grid nodes (i.e., Principal Component Analysis and Linear Discriminant Analysis) are incorporated in the proposed variants to enhance their verification performance. Moreover, local discriminatory power coefficients aiming at separating more efficiently the intra-class matching errors from the inter-class ones are derived at each node. In both approaches we are seeking methods to separate more efficiently feature vectors extracted from frontal facial images of the same person (i.e., the client) and the ones extracted from frontal facial images of the remaining persons in a database (i.e., the impostors). A comparative study of the verification capability of the proposed methods against other frontal face authentication algorithms developed by participating institutes within the EU ACTS M2VTS project is undertaken. The performance of the algorithms is evaluated in terms of their Receiver Operating Characteristic (ROC) and the equal error rate (EER) achieved in the M2VTS database [5]. It is demonstrated that the combined use of local discriminatory power coefficients with MDLA achieves an EER of 3.7 % and is ranked as the best frontal face authentication algorithm in the comparative study undertaken.

## 2 Variants of dynamic link architecture based on mathematical morphology

An alternative to linear techniques for generating an information pyramid is the scale-space morphological techniques. In the following, a brief description of

MDLA and MSD-DLA is given.

In MDLA, we substitute the Gabor-based feature vectors used in dynamic link matching by the *multiscale morphological dilation-erosion* [6]. The multiscale morphological dilation-erosion is based on the two fundamental operations of the grayscale morphology, namely the *dilation* and the *erosion*. Let $\mathcal{R}$ and $\mathcal{Z}$ denote the set of real and integer numbers, respectively. Given an image $f(\mathbf{x}) : \mathcal{D} \subseteq \mathcal{Z}^2 \to \mathcal{R}$ and a structuring function $g(\mathbf{x}) : \mathcal{G} \subseteq \mathcal{Z}^2 \to \mathcal{R}$, the dilation of the image $f(\mathbf{x})$ by $g(\mathbf{x})$ is denoted by $(f \oplus g)(\mathbf{x})$. Its complementary the erosion is denoted by $(f \ominus g)(\mathbf{x})$. Their definitions can be found in any book on Digital Image Processing. The *scaled hemisphere* is employed as a structuring function [6]. The multiscale dilation-erosion of the image $f(\mathbf{x})$ by $g_\sigma(\mathbf{x})$ is defined by [6]:

$$(f \star g_\sigma)(\mathbf{x}) = \begin{cases} (f \oplus g_\sigma)(\mathbf{x}) & \text{if } \sigma > 0 \\ f(\mathbf{x}) & \text{if } \sigma = 0 \\ (f \ominus g_\sigma)(\mathbf{x}) & \text{if } \sigma < 0. \end{cases} \qquad (1)$$

The outputs of multiscale dilation-erosion for $\sigma = -9, \ldots, 9$ form the feature vector located at the grid node $\mathbf{x}$:

$$\mathbf{j}(\mathbf{x}) = ((f \star g_9)(\mathbf{x}), \ldots, f(\mathbf{x}), \ldots, (f \star g_{-9})(\mathbf{x})). \quad (2)$$

An $8 \times 8$ sparse grid has been created by measuring the feature vectors $\mathbf{j}(\mathbf{x})$ at equally spaced nodes over the output of the face detection algorithm described in [7]. $\mathbf{j}(\mathbf{x})$ has been demonstrated that captures important information for the key facial features [8].

Another method for modeling a grayscale facial image region is to employ the morphological signal decomposition (MSD). Let us denote by $f(\mathbf{x}) : \mathcal{D} \subseteq \mathcal{Z}^2 \to \mathcal{Z}$ the facial image region that can be extracted by using a face detection module such as the one proposed in [7]. Without any loss of generality it is assumed that the image pixel values are non-negative, i.e., $f(\mathbf{x}) \geq 0$. Let $g(\mathbf{x}) = 1, \forall \mathbf{x} : \|\mathbf{x}\| \leq \sigma$ denote the structuring function. The value $\sigma = 2$ has been used in all experiments. Symmetric operators will not explicitly denoted hereafter. Given $f(\mathbf{x})$ and $g(\mathbf{x})$, the objective of signal decomposition is to decompose $f(\mathbf{x})$ into a sum of components, i.e., $f(\mathbf{x}) = \sum_{i=1}^{K} f_i(\mathbf{x})$ where $f_i(\mathbf{x})$ denotes the $i$-th component. The $i$-th component can be expressed as:

$$f_i(\mathbf{x}) = [h_i \oplus n_i\, g](\mathbf{x}) \qquad (3)$$

where $h_i(\mathbf{x})$ is the so-called *spine* and

$$n_i\, g(\mathbf{x}) = \underbrace{[g \oplus g \oplus \cdots \oplus g]}_{n_i \text{ times}}(\mathbf{x}). \qquad (4)$$

An intuitively sound choice for $n_1\, g(\mathbf{x})$ is the maximal function in $f(\mathbf{x})$. That is, to choose $n_1$ such that $[f \ominus (n_1 + 1)g](\mathbf{x}) \leq 0, \forall x \in \mathcal{D}$. Thus the first spine is given by $h_1(\mathbf{x}) = [f \ominus n_1\, g](\mathbf{x})$. Morphological signal decomposition can then be implemented recursively as follows.

**Step 1.** Initialisation: $\hat{f}_0(\mathbf{x}) = 0$.

**Step 2.** $i$-th level of decomposition: Starting with $n_i = 1$ increment $n_i$ until

$$\left[(f - \hat{f}_{i-1}) \ominus (n_i + 1)g\right](\mathbf{x}) \leq 0. \qquad (5)$$

**Step 3.** Calculate the $i$-th component by:

$$f_i(\mathbf{x}) = \left\{ \underbrace{\left[(f - \hat{f}_{i-1}) \ominus n_i\, g\right]}_{h_i(\mathbf{x})} \oplus n_i\, g \right\}(\mathbf{x}). \qquad (6)$$

**Step 4.** Calculate the reconstructed image at the $i$-th level of decomposition:

$$\hat{f}_i(\mathbf{x}) = \hat{f}_{i-1}(\mathbf{x}) + f_i(\mathbf{x}). \qquad (7)$$

**Step 5.** Let $\mathcal{A}(f - \hat{f}_i)$ be a measure of the approximation of the image region $f(\mathbf{x})$ by its reconstruction $\hat{f}_i(\mathbf{x})$ at the $i$-th level of decomposition. Increment $i$ and go to Step 2 until $i > K$ or $\mathcal{A}(f - \hat{f}_{i-1})$ is sufficiently small.

A second variant of dynamic link matching is developed that uses feature vectors extracted from the reconstructed images $\hat{f}_i(\mathbf{x})$ at the last $K$ successive levels of decomposition $i = L - K, \ldots, L$ where $L$ denotes the maximal number of decomposition levels, i.e.:

$$\mathbf{j}(\mathbf{x}) = \left(f(\mathbf{x}), \hat{f}_{L-15}(\mathbf{x}), \ldots, \hat{f}_L(\mathbf{x})\right) \qquad (8)$$

where $f(\mathbf{x})$ is the original grey level information. The value $K = 15$ is found to give good results in practice. This variant of DLA is termed Morphological Signal Decomposition-Dynamic Link Architecture.

## 3 Linear projections in variants of dynamic link matching based on mathematical morphology

Two are the most popular linear projection algorithms. The *Karhunen-Loeve or Principal Component Analysis* (PCA) that does not employ category information and the *linear discriminant analysis* (LDA) that exploits the category labels.

First, feature vector dimensionality reduction is pursued by employing PCA. In addition to dimensionality reduction PCA decorrelates the feature vectors and facilitates the LDA that is applied next in eigenvalue/eigenvector computations as well as in matrix inversion. Let $\mathbf{j}^{'}(\mathbf{x}_l) = \mathbf{j}(\mathbf{x}_l) - \mathbf{m}(\mathbf{x}_l)$ be the normalised feature vector at node $\mathbf{x}_l$ where $\mathbf{j}(\mathbf{x}_l) = (j_1(\mathbf{x}_l), \ldots, j_{19}(\mathbf{x}_l))^T$ and $\mathbf{m}(\mathbf{x}_l)$ is the mean feature vector at $\mathbf{x}_l$. Let $N$ denote the total number of frontal images extracted from a database for all persons. Let also $\mathbf{\Gamma}(\mathbf{x}_l)$ be the covariance matrix of the feature vectors $\mathbf{j}^{'}(\mathbf{x}_l)$ at node $\mathbf{x}_l$. In PCA we compute the eigenvectors that correspond to the $p$ largest eigenvalues of $\mathbf{\Gamma}(\mathbf{x})$, say $\mathbf{e}_1(\mathbf{x}_l), \ldots, \mathbf{e}_p(\mathbf{x}_l)$. The PCA projected feature vector is given by:

$$\tilde{\mathbf{j}}(\mathbf{x}_l) = \begin{bmatrix} \mathbf{e}_1^T(\mathbf{x}_l) \\ \vdots \\ \mathbf{e}_p^T(\mathbf{x}_l) \end{bmatrix} \mathbf{j}^{'}(\mathbf{x}_l) = \mathbf{P}(\mathbf{x}_l)\mathbf{j}^{'}(\mathbf{x}_l) \qquad (9)$$

where $T$ denotes the transposition operator. $\tilde{\mathbf{j}}(\mathbf{x}_l)$ is of dimensions $p \times 1$ with $p \leq 19$.

Next LDA is applied to feature vectors produced by PCA. It is well known that optimality in discrimination among all possible linear combinations of features can be achieved by employing Linear Discriminant Analysis (LDA). The feature vectors produced after the LDA projection are called *most discriminating features* (MDFs) [9]. We are interested in applying the LDA at each grid node locally. In the following, the explicit dependence on $\mathbf{x}$ is omitted for notation simplicity. Let $\mathcal{S}$ be the entire set of feature vectors at a grid node and $\mathcal{S}_k$ be the corresponding set of features vectors at the same node extracted from the frontal facial images of the $k$-th person in the database. Our local LDA scheme determines a weighting matrix $(d \times p)$ $\mathbf{V}_k$ for the $k$-th person such that the ratio:

$$\mathcal{M}_k = \frac{\mathrm{tr}\left[\mathbf{V}_k \left\{\sum_{\tilde{\mathbf{j}} \in \mathcal{S}_k} (\tilde{\mathbf{j}} - \tilde{\mathbf{m}}_k)(\tilde{\mathbf{j}} - \tilde{\mathbf{m}}_k)^T\right\} \mathbf{V}_k^T\right]}{\mathrm{tr}\left[\mathbf{V}_k \left\{\sum_{\tilde{\mathbf{j}} \in (\mathcal{S} - \mathcal{S}_k)} (\tilde{\mathbf{j}} - \tilde{\mathbf{m}}_k)(\tilde{\mathbf{j}} - \tilde{\mathbf{m}}_k)^T\right\} \mathbf{V}_k^T\right]} = \frac{\mathrm{tr}\left[\mathbf{V}_k \mathbf{W}_k \mathbf{V}_k^T\right]}{\mathrm{tr}\left[\mathbf{V}_k \mathbf{B}_k \mathbf{V}_k^T\right]} \qquad (10)$$

is minimised where $\tilde{\mathbf{m}}_k$ is the class-dependent mean vector of the feature vectors which result after PCA. This is a generalised eigenvalue problem. Its solution, (i.e., the row vectors $\mathbf{v}_{ik}$ of $\mathbf{V}_k$, $i = 1, \ldots, d$) is given by the eigenvectors that correspond to the $d$ smallest in magnitude eigenvalues of $\mathbf{B}_k^{-1}\mathbf{W}_k$ or equivalently by the eigenvectors that correspond to the $d$ largest in magnitude eigenvalues of $\mathbf{W}_k^{-1}\mathbf{B}_k$ provided that both $\mathbf{W}_k$ and $\mathbf{B}_k$ are invertible. We shall confine ourselves to the case $d = 2$, where only two MDFs are used to simplify the presentation of the method. Because the matrix $\mathbf{W}_k^{-1}\mathbf{B}_k$ is not symmetric in general, the eigenvalue problem could be computationally unstable. A very elegant method that diagonalises the two symmetric matrices $\mathbf{W}_k$ and $\mathbf{B}_k$ and yields a stable computation procedure for the solution of the generalised eigenvalue problem has been proposed in [9]. This method has been used to solve the generalised eigenvalue problem.

Let the superscripts $t$ and $r$ denote a test and a reference person (or grid), respectively. Let us also denote by $\mathbf{x}_l$ the $l$-th grid node. Having found the weighting matrix $\mathbf{V}_k(\mathbf{x}_l)$ for the $l$-th node of the $k$-th person in the database, we project the reference feature vector after PCA at this node onto the plane defined by $\mathbf{v}_{1k}(\mathbf{x}_l)$ and $\mathbf{v}_{2k}(\mathbf{x}_l)$ as follows:

$$\breve{j}(\mathbf{x}_l^r) = \mathbf{V}_k \left[\mathbf{P}(\mathbf{x}_l^r)\left(\mathbf{j}(\mathbf{x}_l^r) - \mathbf{m}_l\right) - \tilde{\mathbf{m}}_{kl}\right]. \qquad (11)$$

Let us suppose that a test person claims the identity of the $k$-th person. Then the test MDF vector at the $l$-th node can be derived as in (11). The $L_2$ norm of the difference between the MDF vectors at the $l$-th node has been used as a (signal) similarity measure, i.e.:

$$C_v(\breve{j}(\mathbf{x}_l^t), \breve{j}(\mathbf{x}_l^r)) = \|\breve{j}(\mathbf{x}_l^t) - \breve{j}(\mathbf{x}_l^r)\| \qquad (12)$$

Let us denote by $\mathcal{V}$ the set of grid nodes. The grid nodes are simply the vertices of a graph. Let also $\mathcal{N}(l)$ denote the four-connected neighbourhood of vertex $l$. The objective is to find the set of test grid node coordinates $\{\mathbf{x}_l^t,\ \ l \in \mathcal{V}\}$ that yields the best matching. As in DLA [2], the quality of the match is evaluated by taking into account the grid deformations as well. Grid deformations can be penalised using the additional cost function:

$$C_e(l, \xi) = C_e(\mathbf{d}_{l\,\xi}^t, \mathbf{d}_{l\,\xi}^r) = \|\mathbf{d}_{l\,\xi}^t - \mathbf{d}_{l\,\xi}^r\| \quad \xi \in \mathcal{N}(l) \qquad (13)$$

with $\mathbf{d}_{l\,\xi} = (\mathbf{x}_l - \mathbf{x}_\xi)$. The penalty (13) can be incorporated to a cost function:

$$C(\{\mathbf{x}_l^t\}) = \sum_{l \in \mathcal{V}} \left\{ C_v(\breve{j}(\mathbf{x}_l^t), \breve{j}(\mathbf{x}_l^r)) + \lambda \sum_{\xi \in \mathcal{N}(l)} C_e(l, \xi) \right\}. \qquad (14)$$

One may interpret the optimisation of (14) as a simulated annealing with an additional penalty (i.e., a constraint on the objective function). Since the cost function (13) does not penalise translations of the whole graph the random configuration $\mathbf{x}_l$ can be of the form of a random translation $\mathbf{s}$ of the (undeformed) reference grid and a bounded local perturbation $\mathbf{q}_l$, i.e.:

$$\mathbf{x}_l^t = \mathbf{x}_l^r + \mathbf{s} + \mathbf{q}_l \quad ; \quad \|\mathbf{q}_l\| \leq q_{\max} \tag{15}$$

where the choice of $q_{\max}$ controls the rigidity/plasticity of the graph. It is evident that the proposed approach differs from the two stage coarse-to-fine optimisation procedure proposed in [2]. In our approach we replace the two stage optimisation procedure with a probabilistic hill climbing algorithm which attempts to find the best configuration $\{\mathbf{s}, \{\mathbf{q}_l\}\}$ at each step.

## 4 Derivation of discriminatory power coefficients weighting the node contributions

It is well known that some grid nodes which coincide with key facial features (e.g. the eyes, the nose) play a more crucial role in the verification procedure than other nodes. Thus, it would be helpful to calculate a weighting coefficient for each node according to its discriminatory power. We would like to weigh the signal similarity measure at node $l$ given by:

$$C_v(\mathbf{j}(\mathbf{x}_l^t), \mathbf{j}(\mathbf{x}_l^r)) = \|\mathbf{j}(\mathbf{x}_l^t) - \mathbf{j}(\mathbf{x}_l^r)\| \tag{16}$$

using class-dependent discriminatory power coefficients (DPCs) $DP_l(\mathcal{S}_r)$ so that when person $t$ claims the identity of person $r$ a distance measure between them is computed by:

$$D(t,r) = \sum_{l \in \mathcal{V}} \frac{DP_l(\mathcal{S}_r)\, C_v(\mathbf{j}(\mathbf{x}_l^t), \mathbf{j}(\mathbf{x}_l^r))}{\sum_{n \in \mathcal{V}} DP_n(\mathcal{S}_r)} \tag{17}$$

with $\mathcal{S}_r$ denoting the class of the reference person $r$. Let $m_{\text{intra}}(\mathcal{S}_r, l)$ be the mean intra-class matching error for the class $\mathcal{S}_r$ and $m_{\text{inter}}(\mathcal{S}_r, l)$ be the mean inter-class matching error between the class $\mathcal{S}_r$ and $\mathcal{S} - \mathcal{S}_r$ at grid node $l$:

$$\begin{aligned} m_{\text{intra}} &= E\left\{C_v(\mathbf{j}(\mathbf{x}_l^t), \mathbf{j}(\mathbf{x}_l^r))\right\} \; \forall t,\, r \in \mathcal{S}_r & (18) \\ m_{\text{inter}} &= E\left\{C_v(\mathbf{j}(\mathbf{x}_l^t), \mathbf{j}(\mathbf{x}_l^r))\right\} \; \forall r \in \mathcal{S}_r,\, t \in (\mathcal{S} - \mathcal{S}_r) \end{aligned}$$

where $\mathcal{S}$ denotes the set of all classes in the database. Let $\text{var}_{\text{intra}}(\mathcal{S}_r, l)$ and $\text{var}_{\text{inter}}(\mathcal{S}_r, l)$ be the variances of the intra-class matching errors and the inter-class matching errors given by (16), respectively. A plausible measure of the discriminatory power of the grid node $l$ for the class $\mathcal{S}_r$ is the *Fisher's Linear Discriminant* (FLD) function defined on the node distances:

$$DP_l(\mathcal{S}_r) = \frac{(m_{\text{inter}}(\mathcal{S}_r, l) - m_{\text{intra}}(\mathcal{S}_r, l))^2}{\text{var}_{\text{inter}}(\mathcal{S}_r, l) + \text{var}_{\text{intra}}(\mathcal{S}_r, l)}. \tag{19}$$

We can see that in (19) the $DP_l(\mathcal{S}_r)$ is maximised when the denominator $\text{var}_{\text{inter}}(\mathcal{S}_r, l) + \text{var}_{\text{intra}}(\mathcal{S}_r, l)$ is minimised. This can be interpreted as an **AND** rule for the variances of the matching errors clusters. Alternatively, one can use a more relaxed criterion of the form:

$$DP_l(\mathcal{S}_r) = \frac{(m_{\text{inter}}(\mathcal{S}_r, l) - m_{\text{intra}}(\mathcal{S}_r, l))^2}{\sqrt{\text{var}_{\text{inter}}(\mathcal{S}_r, l)\text{var}_{\text{intra}}(\mathcal{S}_r, l)}}. \tag{20}$$

The denominator of (20) is interpreted as an **OR** rule for the variances of matching error clusters.

## 5 Performance evaluation of the combined schemes

The combined schemes of MDLA/MSD-DLA with linear projections and discriminatory power coefficients have been tested on the M2VTS database [5]. The database contains both sound and image information. Four recordings (i.e., shots) of the 37 persons have been collected. In our experiments, the sequences of rotated heads have been considered by using only the luminance information at a resolution of 286 × 350 pixels. In the authentication experiments we use only one frontal image from the image sequence of each person that has been chosen based on symmetry considerations. Four experimental sessions have been implemented by employing the "leave one out" principle. Details on the experimental protocol used in the performance evaluation as well as on the computation of thresholds that discriminate each person from the remaining persons in the database can be found in [8]. We may create a plot of False Rejection Rate (FRR) versus the False Acceptance Rate (FAR) with the varying thresholds as an implicit parameters. This plot is the *Receiver Operating Characteristic* (ROC) of the verification technique. The ROCs of the MDLA with and without linear projections or discriminatory power coefficients are plotted in Figure 1. In the same plot the ROCs of MSD-DLA with and without discriminatory power coefficients are also depicted. The Equal Error Rate (EER) of a technique (i.e., the operating state of the method when FAR equals FRR) is another common figure of merit used in the comparison of verification techniques.

The EER of MDLA with one MDF is 6.8% and with two MDFs is 5.4% whereas the EER of MDLA without any linear projections is 9.35 % [8]. It is seen that the incorporation of linear projections improves the EER by 2.55-4%. Moreover, the EER of MDLA is found to be 3.7 % when the discriminatory power coefficients (19) are used. A drop of 5.65% occurs in this case.

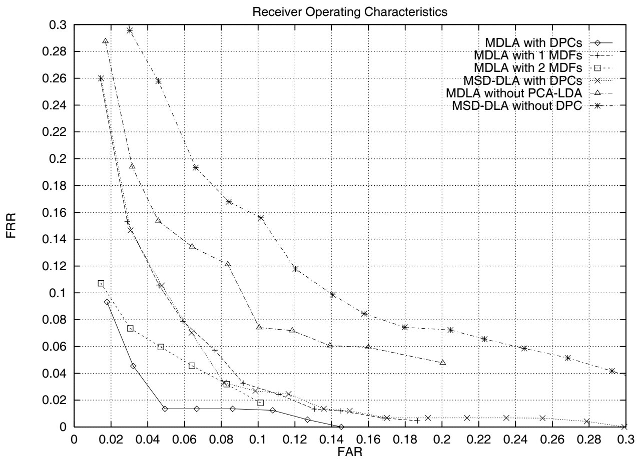


Figure 1: Receiver Operating Characteristics of MDLA and MSD-DLDA with/without linear projections or local discriminatory power coefficients.

It is worth noting that the EER of MSD-DLA without local discriminatory power coefficients is 11.89 %. By using this discrimination criterion (19), we achieve an EER of 6.73% following the same experimental protocol. When the discrimination criterion (20) is used, the EER is 6.58%. Accordingly, a significant drop of 5.3% in EER is reported.

The best EERs achieved by frontal face authentication algorithms developed within M2VTS project are tabulated in Table 1. It is seen that the proposed MDLA with DPCs is ranked as the first method in terms of EER.

Table 1: Best EERs achieved by frontal face authentication algorithms within M2VTS project.

| Method | EER (%) |
|---|---|
| morphological dynamic link architecture with discriminatory power coefficients | 3.7 |
| Optimised robust correlation [10] | 4.8 |
| Elastic graph matching based on Gabor wavelets with local discriminants [11] | 5.4 |
| Grey level frontal face matching [12] | 8.5 |

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