

Evaluation of Individuals Identification using Facial recognition methods based on a Reference image

Nadjima Said Hassani*, **Ziyang Zhen***,*College of Automation Engineering,Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

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Abstract

Surveillance systems are becoming more common in urbanized areas, and high-performance automated solutions are essential. This automation enables the proliferation of cameras in systems while keeping up with the rise of people involved in the capture environment. Individual identification can be performed by recognizing faces, necessitating advanced and robust approaches to avoid errors in the Classification of people discovered. This paper tackles some of the most prevalent facial recognition challenges and the process modifications required to achieve better recognition criteria. The proposed strategies are evaluated using a face database from the literature and standard performance measures for the classifiers utilized.

Keywords: Image extraction, Classification, convolutional neural network, Facial recognition.

I. Introduction

In order to improve advanced security systems, such as in airports, it is now possible to use face recognition methods that allow faster identification of marked individuals in a watch-list screening, for instance. However, the registration of these individuals in the system is often limited by a reduced quantity of reference images. In general, only one image is available to represent a particular individual, which makes the training of the system much more complex due to the limitation of information. Performance analysis of several algorithms is necessary to sustain the best ones to benefit from an operational and efficient system. Therefore, this research aims to explore several of the techniques forming state-of-the-art in the field of face recognition to reason more promising sources for the explored case. Specific classification approaches, in particular, are modeled and then progressively improved to proceed toward a system capable of identifying individuals with the maximum accuracy rate. Furthermore, considerable work is spent researching the performance of facial feature extraction approaches. As a result, it is feasible to combine many representative face descriptors of individuals simultaneously, simplifying the work of classifying and identifying them.

This article will present a quick contextualization of common issues in face recognition before moving on to the statement of objectives. The methods provided for performance evaluation, as well as the techniques studied, will be presented. Then, the results obtained from each evaluated technique will be illustrated according to various performance measures to continue with a discussion on the research project's progress. A proposal about possible developments will finally be formulated to plan future paths for improving the systems assessed.

II. Overview

Face recognition systems are usually subdivided into three significant steps:

- 1) Face detection and basic image pre-processing to extract one or more regions of interest
- 2) feature extraction followed by normalization operations to form descriptor vectors
- 3) feature Classification to identify individuals' faces in the form of a decision score.

Depending on the algorithms used, some processes may combine steps. These face recognition systems face several significant obstacles relating to the image acquisition environment and the face evaluation approaches that have been discovered. Furthermore, light issues, position, and multivariate expression on the faces to be detected make the configuration extremely complex. Image acquisition can also occur in various controlled capture situations, adding extra challenges in terms of image resolution, the incorporation of movement in the scene, and some cases of face occlusion [1].

In the case of airport security systems, it is frequently necessary to be able to register a new person in a reference base (gallery) using a single reference image, often a passport photo. However, due to the regulatory processes for passport images, this reference image must be acquired in a controlled environment where the lighting is perfect, a frontal pose of the face is guaranteed, no facial expression is present, and it is generally acquired using a camera with excellent image resolution.

Security camera systems, on the other hand, bring several variations of illumination from room to room, produce several angles of exposure according to their position relative to the individual, are usually of lower resolution, and are affected by uncontrolled expressions, occlusions by objects on faces or by other individuals, and the effects of artifacts related to movements. Furthermore, because of the vast number of people in the area, when camera systems detect individuals on the scene, they generate many requests (probes) for the identification of each face. These identification requests must then be processed and reviewed in a reasonable amount of time against a list of known faces to make choices with high certainty. As a result, it is essential to separate persons from one another very well and according to a steadily growing checklist. Processes that require a long processing time should be avoided in this area, even if they occasionally benefit from a more rigorous inspection of the faces identified.

Acquisition in the environment typically uses many images of the same face across time, whereas the reference frequently consists of a single image of the face for system registration. This particular situation (Single Sample Per Person) offers another significant problem in the context of facial recognition in security systems, as the lack of reference information for each individual severely limits the system's training potential by identifying entries. Approaches for generating synthetic images can be used to fill in the gaps. However, it remains challenging to obtain such images while guaranteeing that they accurately reflect the human without providing false representations of the person.

All of the obstacles described above in face recognition procedures imply that the conceptualized systems must employ advanced and efficient strategies to achieve feature extraction and Classification of persons. The techniques used to execute this operation must be carefully chosen because the faces, which are relatively similar because of their shapes and looks, tend to be highly grouped in the augmented feature space (feature space).

Face recognition systems are reliant on accurate feature extraction. This is why many descriptors have been established despite the difficulties of capturing faces in the surroundings. In order to allow constant descriptor extraction despite changing acquisition settings, recognized approaches for characterizing faces frequently strive to be invariant to the illumination, rotation, and scale conditions present in the images. Various methods already available use diverse concepts such as principal component analysis in a high feature space, texture pattern recognition, gradient frequency evaluation, color analysis, facial geometry, and even some hybrids of numerous techniques [2]. Other methods, such as image alterations, synthetic generation, or 3D models of faces [3,4], seek to reproduce observed variations in lighting, position, or expression. The variety of methods investigated in the literature for face recognition reflects the task's complexity and the range of possible applications in this subject.

Following the various feature extraction approaches for representing faces comes different classification algorithms used to distinguish the required individual from the baseline. As a result, these classification procedures are closely related to the previously employed approaches to characterize the data to be classified. Many conventional classification approaches are often relevant to standard examples of face recognition when faces are represented in digital form in memory. On the other hand, when just one reference image per individual is provided for training, some techniques suffer significantly from a lack of data. Another critical concern for data classification in a face recognition surveillance system is that the classifier must support online learning, which means that the system is constantly learning, i.e., while the system is in service, it is always teaching new people to recognize. The two preceding criteria imply that several adjustments must usually be made to the classification methods used to perform face recognition; otherwise, the usual methods rely on a large amount of training data or require complete retraining of the system when adding additional data, becoming inapplicable. Classifiers must necessarily allow for gradual and quick adaptation to new knowledge only available in limited amounts. The concepts described in this section justify several of the choices taken during this study and are discussed in subsequent sections.

III. Research Objective

The specific goal of this project is to evaluate both methods for feature extraction and face Classification of individuals learned in a reference database to identify potential sources of future developments. Since the classification algorithm is closely related to the descriptor extraction method, both aspects are treated simultaneously. Therefore, the project consists of an effort to model standard techniques in the literature to accomplish face recognition which can then be used in a surveillance system.

More precisely, a reference system (*baseline*) that employs a classifier by the nearest neighbor (Nearest Neighbor, 1-NN) and extraction of features LBP (Local Binary Patterns) has been realized

during past works. Although the results are intriguing, better strategies are needed to improve the overall efficiency of the face recognition system.

This research evaluates and compares novel methodologies to the core model to discover potential areas for improvement.

IV. Methodology

This section presents various information related to the methodology currently used to perform face recognition and the future techniques planned for improving the process.

A. Dataset

The images used to evaluate the performance of the face recognition algorithms developed during the project can use a large bank of existing databases. A detailed list very well of several of the existing bases. In the context of this project, the *Color FERET* face database [5] is more specifically used because of its diversity of images. It is an expansion with higher-resolution color images of the original *FERET* grayscale database. The old images in shades of gray are therefore incorporated into it. Its characteristics are listed as follows:

- Offers a very rigorous annotation which makes its use very interesting.
- Allows the study of a wide range of acquisition conditions since the images are acquired, for each individual, according to various poses and levels of illumination, as well as in the presence of expression or not.
- Includes various ethnicities, making it possible to evaluate the system's performance according to a diversified population.
- Allows the study of the evolution of faces over time since the images were acquired over fifteen photographic sessions spread over three years.
- Contains a total of 994 individuals assigned a unique identification number. Each individual in the *Color FERET* database contains at least one frontal reference image, without expression, and ideally lit to represent the "passport" type image sought for the registration of the individual in the checklist during the system drive. Each of the images is saved at a high resolution of 512x768 pixels. However, the faces are positioned at various distances from the camera lens, making it possible to assess the robustness of the algorithms at scale.



Fig. 1 Detection of individual "00690" faces from the *Color FERET* database with the Viola-Jones algorithm according to various poses and expressions visible on the face.

B. Tools Used in Development

In order to develop the applications allowing to test the various algorithms involved, the *EmguCV* library is employed first in order to use several of the standard functionalities of the *OpenCV* open source code, but under a C# environment. This environment is chosen primarily because it corresponds to the one used for developing past projects, which allows rapid reuse of specific implemented methods. In addition, this environment allows fast and highly optimized image

processing thanks to the integration of graphics cards by employing the *CUDA* platform when analyzing large data structures and images while offering a reasonably user-friendly syntax.

To design some of the classifiers, the corresponding libraries are sometimes employed. For example, research efforts related to the evaluation of *SVMs* for Classification use the *LIBSVM* library [6]. Libraries or even portions of free source code specific to certain algorithms are used when these are not directly available from the resources included in *EmguCV*.

C. Face Detection And Processing

The *Viola-Jones (JV)* detection method is used to detect the position of the faces in images in order to obtain a region of interest from which the feature vectors can be extracted. This system is built on a succession of cascading weak classifiers that were previously trained using the *AdaBoost* technique to enable robust and quick face detection.

Following *Viola-Jones* face detection, the resulting regions of interest are re-sized to 256x256 pixels using bi-linear interpolation to provide continuous reference pictures for feature extraction. Then, in the case of the baseline system using *LBP* descriptors, a conversion to gray tones and histogram equalization are utilized to create normalized regions of interest before feature extraction.

D. Feature Extraction And Normalization

The evaluation of faces in this research is accomplished by considering the face as a whole. Therefore, features are extracted for the entire face contained in the region found with *Viola-Jones* without attempting to represent geometric relationships between eyes, nose, and mouth.

1) Extraction of LBP features

The first feature extraction method employed by the face recognition system is to apply the *LBP* algorithm [7]. This descriptor, invariant to variations in intensity thanks to its local encoding, analyzes the textures present in the image, making it possible to describe the face it contains. In the specific case of the *LBP* implementation used, the number of features composing the vector is $\varnothing = 59$ since only the patterns that represent textures commonly observed in nature are preserved, which allows a group of all the unusual patterns, like alternating black-white lines, in a final band called "others" [7]. This technique makes it possible to reduce similar and compressed descriptor vectors without however suffering from any loss of relevant information to characterize faces.

2) HOG feature extraction

In order to explore new feature extraction methods to improve face recognition performance, a HOG descriptor [8, 9] is considered the second method in this project.

This technique accomplishes a representation of faces using histogram analysis of the gradients present in the image. The region of interest where the face is detected is subdivided into blocks of equal sizes, and these are also subdivided in turn into cells. For each cell, a pixel gradient analysis is performed to form a nine-band gradient histogram. Several techniques for recombining histograms into vectors exist in the literature. In the case of this project, a new histogram is created from each block independently by recombining the histograms of its corresponding cells. Then, by positioning the gradient accumulators of these various histograms for all the blocks, we obtain the vector of facial characteristics. In the particular case of the project, blocks of 64x64 and cells of 16x16 are employed so that the resulting vector contains, in total, $\varnothing = 144$ features to represent the face according to the *ROIs* of 256x256 pixels that were previously established.

3) CNN Feature Extraction

Finally, a third feature extraction method is considered. This is based on using a convolutional neural network (CNN). The idea, in this case, is that rather than imposing an image processing technique based on a priori knowledge of the domain and which possibly makes incorrect assumptions about the understanding of the data, the task is left to a CNN, which will itself learn how to extract the essential features to represent a face using deep learning. CNN will then ensure that it does not make any assumptions about the importance of the features. Therefore, the descriptor vectors obtained theoretically become as discriminating as possible while becoming specific to the case of face recognition. In order to avoid performing the heavy task of designing and training this type of network on an immense quantity of face images, the pre-trained *CNNVGG* Face Descriptor [10] was recovered. Then, since this *CNN* is trained to classify the faces of particular individuals from another database, ultimately, we discard the few output layers performing the final Classification of individuals to preserve only the outputs from a sub-layer that emits its output values corresponding to the desired feature vectors. These values can then be redirected with the classifier of our choice in order to accomplish a new face training specific to our case. The *CNN* descriptor initially produces a vector with $f= 4096$ components.

On the other hand, an additional layer available at the end of the *CNN* performs recombination of the features containing the relevant information in a similar way to the *PCA* technique, which makes it possible to reduce the descriptor to $f= 259$ components. This last vector is, therefore, the one used for Classification with *CNN*. Also, the procedures for using *VGG* networks indicate that the images must be re-sized to 224x224 and be pre-normalized by removing the average pixel value of all the images from the training base. Thus, all the *ROIs* captured by Viola-Jones are re-sized to meet the requirements of the *CNN* inputs, and the pixels are reduced by $(103.939,116.779,123.68)_{BGR}$ before applying the *CNN* as a descriptor.

For all three techniques mentioned, a normalization step of the resulting feature vectors is performed before proceeding to the classification step. To accomplish the normalization, equation (1) is used, which represents the index of the features forming the vectors (templates) and represents the individuals to be recognized by the face recognition system.

$$t_k^{norm}(i) = \frac{t_k(i) - \arg \min_i t_k(i)}{\arg \max_i t_k(i) - \arg \min_i t_k(i)}$$

Thus, it is possible to see with the normalization equation that the vectors are reported in the range [0,1] for all the corresponding characteristics between the multiple vectors that will form the training basis. By proceeding by a group of corresponding characteristics rather than by a global normalization of all the values on the set of vectors, we normalize respectively to each of the components of the vectors, which improves the performances.

E. Classification of individuals

In order to accomplish the Classification of specific faces of individuals in the *Color FERET* database, two types of classifiers are involved in the analysis of this project, namely the reference model previously conceptualized with the nearest neighbor rule (*Nearest Neighbor, 1-NN*) and the use of Support Vector Machines (*SVM*). On the other hand, regardless of which of the two models is used,

the internal architecture used to represent each individual to be recognized with the face recognition surveillance system is the same.

1) Classifier *I-NN*

The *I-NN* approach employs a Euclidean distance adjusted by a normalization weight according to the number of features forming the descriptor vector, as proposed in and represented by equation (2). To this equation, the subscript *i* represents the features, and the subscript *j* corresponds to the faces of the new individuals (probe) to be tested for identification. These probes are represented by vectors *a* obtained using the same extraction method used to obtain the template *k* trained in the face recognition system for the *n* individuals to be stored in the gallery.

$$S_{j,k} = 1 - \sqrt{\frac{1}{f} \sum_{i=1}^f x(a_{j,i} - t_{k,i})^2}$$

The Euclidean distance being normalized by the number of features in the vectors makes it possible to subtract it from 1 to obtain a similarity score recorded in a *n* matrix for all probe template combinations specified as input.

2) *SVM* classifier

The use of *SVM* classifiers should allow us to obtain better face classification results by employing an adequate kernel for separating non-linearly separable data. This is why we use this classifier to evaluate this study. The implementation of *SVM* has also already been demonstrated in face recognition, which means that their application in the context of the surveillance system is entirely justified.

However, significant difficulty in a face recognition system operating in a Single Sample Per Person context is the significant imbalance of positive data (the template of the individual) compared to harmful data (all the other vectors available). Also, to better isolate an individual from others using its corresponding *SVM*, the set of images from the *Color FERET* database is used to help train each *SVM*.

Following the training of the separation margins with the support vectors, the *SVM* classifiers use a probabilistic output, allowing them to obtain a classification score for each individual. Thus, obtaining the same similarity matrix *s* as obtained with *I-NN* classifiers is possible.

F. Complete face recognition system

Since both the *I-NN* classifier and the *SVMs* output a similarity matrix for all probe-template combinations and use the same input templates, these can quickly be interchanged within the same development application. Similarly, feature extraction methods use the same regions of interest as input to produce similar vectors as their output. This, therefore, makes these two parts very modular for the evaluation in a combination of the best techniques. It also ensures that method benchmark tests are well controlled since they use the same intermediate procedures for face detection, *ROI* re-sizing, and vector normalization since the same code and functions are used.

G. Evaluation test and measure

In order to evaluate the performance of methods used in face recognition systems, three types of tests are performed using *Color FERET* data. Each test run is based on ten replications that

alternately train the system to recognize the faces of some randomly selected individuals and then test the classification results by presenting both known and unknown people to the classifiers. The three tests used for system evaluation each have a specific purpose. The first is used to assess expression variations on the faces of individuals trained in the system with expressionless "passport" type images. The second similarly evaluate the faces of individuals but for pose variations. The third varies the number of individuals trained in the gallery to observe the impact of adding more or fewer faces to the system or to check whether the classification error rate varies drastically with more or fewer individuals represented.

V. Results

This section presents both the current advancements of the project that the future developments planned according to the encountered difficulties.

Table 1 Average results over ten replications for some evaluated face recognition systems depending

	FE: <i>LBP</i> ₅₉ , FC: 1- NN		FE: <i>HOG</i> ₁₄₄ , FC: 1-NN		FE: <i>CNN</i> ₂₅₉ , FC: 1-NN		FE: <i>LBP</i> ₅₉ , FC: SVM		FE: <i>HOG</i> ₁₄₄ , FC: SVM						
	<i>pAUC</i> ₁₀	AU C	AU PR	<i>pAUC</i> ₁₀	AU C	AU PR	<i>pAUC</i> ₁₀	AU C	AU PR	<i>pAUC</i> ₁₀	AU C	AU PR	AU C	AU PR	
Expression (Test #1)	0.868 (0.009)	0.9 (0.04)	0.66 (0.10)	0.802 (0.008)	0.9 (0.03)	0.59 (0.17)	0.495 (0.013)	0.8 (0.06)	0.18 (0.13)	0.839 (0.010)	0.9 (0.05)	0.49 (0.02)	0.839 (0.01)	0.933 (0.005)	0.49 (0.00)
Position (Test #2)	0.437 (0.013)	0.8 (0.04)	0.18 (0.00)	0.420 (0.011)	0.8 (0.07)	0.15 (0.12)	0.189 (0.013)	0.6 (0.09)	0.01 (0.00)	0.533 (0.013)	0.7 (0.08)	0.09 (0.00)	0.53 (0.01)	0.78 (0.00)	0.09 (0.00)
N=10	0.895 (0.017)	0.9 (0.06)	0.74 (0.26)	0.890 (0.082)	0.9 (0.08)	0.65 (0.31)									
Trained individuals (Test #3)	0.884 (0.013)	0.9 (0.05)	0.64 (0.07)	0.832 (0.016)	0.9 (0.04)	0.58 (0.06)									
N=50	0.885 (0.008)	0.9 (0.02)	0.71 (0.11)	0.838 (0.009)	0.9 (0.03)	0.65 (0.20)									

on various algorithms (FE: feature extraction, FC: face classifiers).

A. DISCUSSIONS

Using the test methodologies described in the preceding section, it was possible to cover many of the critical application circumstances for using face recognition in an automated surveillance system, such as variations in expression, pose, or the number of individuals registered in the system. Table 1 shows the results of numerous face recognition system test combinations using the LBP, *HOG*, and *CNN* algorithms for feature extraction, as well as the *1-NN* and *SVM* classifiers mentioned in earlier sections. In some cases, the tests are not further investigated because the previous results were not conclusive to justify completing the tests. The graphs of the *ROC* and *PR* curves corresponding to the results of this table are presented in the appendix. In general, the baseline *1-NN* system, in combination with *LBP*, remains the most efficient despite the improvement attempts explored during the project. It would therefore seem that the simplicity of the two techniques still predominates compared to the other algorithms explored during the project.

The results demonstrate several interesting facts, such as the inability of all the systems to remain very robust with pose variations (*test #2*), which is illustrated by significant performance drops compared to the other two tests. On the other hand, by analyzing the distributions of scores obtained, we quickly notice how the distributions are not exceptionally well separated, which limits the decision between accepting or refusing the recognition of individuals.

B. DIFFICULTIES ENCOUNTERED

CNN descriptors have been particularly difficult to implement, considering that these were only available

only under *MATLAB* codes or external *C++* libraries that were not compatible with the project initially used. Thus, various libraries had to be implemented and compiled to transfer the parameters and results between the *C#* interface and the *MATLAB* code converted into *C* thanks to its compiler. This descriptor is the worst performer of the three evaluated based on cumulative results. This is quite surprising considering that it should technically adapt to the specific case of face recognition for which it is trained since it learns to extract relevant features from faces to distinguish them better. It is, therefore, very likely that specific details, such as the image resolution used as input or that the type of face capture conditions depending on the lighting and the pose, are too different between the *CNN* training images and those used for the tests, which could explain its weaker performance. Thus, it is possible that personalized retraining in the particular case targeted with *Color FERET* is necessary to make this method more effective.

Developments related to the use of *SVMs* during this project are still unsatisfactory since these do not currently produce results superior to the *1-NN* used as a baseline, regardless of the type of descriptor used. We notice with the results that the *SVMs* tend more easily to predict antagonistic classes only with slight variations of the recognition threshold. This drops the system's accuracy faster than with *1-NNs*, producing slightly weaker results, as shown in the corresponding sections of Table 1. Thus, the imbalance between the positive and negative is still problematic for the proper use of *SVMs* in the context of this project. Several adjustments have been attempted to counter this problem, such as adding various synthetic faces and using better representations of the faces of negative individuals for training. Although each adjustment did help improve performance, the multiple retries performed were still insufficient for the *SVMs* to outperform the similarity scores achieved with the *1-NNs*.

C. FUTURE DEVELOPMENTS

Several ways of improvement have been considered, such as using extraction of characteristics according to local regions on the faces (patch-based) [13], which would make it possible to apply weighting weights on various parts of the face to give more importance to specific regions that are more discriminating than others, such as the eyes, nose, and mouth compared to the cheeks and forehead. It would also make it possible to consider the importance of the various parts of the face and to emphasize the more discriminating features concerning each person by considering the particular shapes of the face as well as the relative location of these patches, which is information very often lost due to histogram combinations of textures or gradients with *LBP* and *HOG* respectively. Finally, a particular application of *SVMs*, the Ensemble of *Exemplar-SVMs*, is the next classifier planned under consideration for this project.

This method is specifically designed to solve problems involving a massive imbalance between the positive and negative training classes and aims to find linear separator planes that effectively isolate an exemplar from a large cohort of counterexamples.

VI. CONCLUSION

During the writing of this article, the classification methods by Nearest Neighbor and Support Vector Machines, as well as the extraction of descriptors by Local Binary Patterns, Histogram of Oriented Gradients, and Convolutional Neural Networks, all intended for a performance study, were discussed. The algorithms involved in each case have been briefly presented to understand better their mode of operation and the challenges involved. All the techniques considered have been chosen to produce an increasingly efficient face recognition system. The various issues involved in acquiring images in the environment in face recognition have been addressed to demonstrate the importance of the robustness of the algorithms used in the process. The rest of the project will therefore consist of developing some of the improvements mentioned and other solutions that could be discovered later.

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References

- [1] T. Bourlai, "Face Recognition Across the Imaging Spectrum," ed: Springer, 2016.
- [2] P. F. De Carrera and I. Marques, "*Face recognition algorithms*," *Master's thesis in Computer Science, Universidad EuskalHerriko*, 2010.
- [3] A. S. Georghiadis, P. N. Belhumeur, and D. J. Kriegman, "From few to many: *Illumination cone models for face recognition under variable lighting and pose*," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 23, pp. 643-660, 2001.

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- [4] C. Pagano, E. Granger, R. Sabourin, A. Rattan, G.-L.Marcialis, and F. Roli, "*Efficient adaptive face recognition systems based on capture conditions*," in Computational Intelligence in Biometrics and Identity Management (CIBIM), 2014 *IEEE Symposium on*, 2014, pp. 60-67.
- [5] P. J. Phillips, H. Moon, S. Rizvi, and P. J. Rauss, "*The FERET evaluation methodology for face-recognition algorithms*," Pattern Analysis and Machine Intelligence, *IEEE Transactions on*, vol. 22, pp. 1090-1104, 2000.
- [6] C.-C. Chang and C.-J. Lin, "*LIBSVM: a library for support vector machines*," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 2, p. 27, 2011.
- [7] G. Zhao and M. Pietikainen, "*Dynamic texture recognition using local binary patterns with an application to facial expressions*," Pattern Analysis and Machine Intelligence, *IEEE Transactions on*, vol. 29, pp. 915-928, 2007.
- [8] M. Bicego, A. Lagorio, E. Grosso, and M. Tistarelli, "*On the use of SIFT features for face authentication*," in 2006 *Conference on Computer Vision and Pattern Recognition Workshop (CVPRW'06)*, 2006, pp. 35-35.
- [9] O. Déniz, G. Bueno, J. Salido, and F. De la Torre, "*Face recognition using histograms of oriented gradients*," Pattern Recognition Letters, vol. 32, pp. 1598-1603, 2011.
- [10] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "*Deep face recognition*," *Proceedings of the British Machine Vision*, vol. 1, p. 6, 2015.
- [11] C. Pagano, E. Granger, R. Sabourin, A. Rattan, G.-L.Marcialis, and F. Roli, "*Efficient adaptive face recognition systems based on capture conditions*," in Computational Intelligence in Biometrics and Identity Management (CIBIM), 2014 *IEEE Symposium on*, 2014, pp. 60-67
- [12] S. Bashbaghi, E. Granger, R. Sabourin, and G. A. Bilodeau, "*WatchList Screening Using Ensembles Based on Multiple Face Representations*," in Pattern Recognition (ICPR), 2014 22nd International Conference on, 2014, pp. 4489-4494.
- [13] C. Pagano, E. Granger, "*Adaptive ensembles for face recognition in changing video surveillance environments*," Information Sciences, vol. 286, pp. 75101, 2014.

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