

# A Comparison of Histogram and Template Matching for Face Verification

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## Abstract

*Face identification and verification are parts of a face recognition process. The verification of faces involves the comparison of an input face to a known face to verify the claim of identity of an individual. Hence, the verification process must determine the similarity between two face images, a face object image and a target face image. In order to determine the similarity of faces, different techniques can be used, such as methods based on templates and histograms. In real-world applications, captured face images may suffer variations due to disturbing factors such as image noise, changes in illumination, scaling, rotation and translation. Because of these variations, face verification becomes a complex process. In this context, a comparison between histogram and template matching methods is done in this work using images with variations. Different experiments were conducted to analyze the behavior of these methods and to define which method performs better in artificially generated images.*

## 1. Introduction

Face recognition is one of the extensively researched areas in computer vision in the last three decades. Even though some works related to the automatic machine recognition of faces started to appear in the 1970's, it is still an active area that needs extensive research effort [16] and has been receiving significant attention from both public and private research communities [14].

The face recognition process normally solves the problem of identification, in which a given unknown face image is compared to images from a database of known individuals to find out a correct match. Face recognition also solves the problem of face verification in which a known face is re-

jected or confirmed to check the identity of an individual. In both cases, the comparison of two face images, a face object image (FOI) and a target face image (TFI), is necessary to determine the similarity.

Face recognition becomes a challenging task due to the presence of factors that affect images like changes in illumination, pose changes, occlusion, presence of noise due to imaging conditions and imaging orientations. Variations caused by these disturbing factors can influence and change the overall appearance of faces and, consequently, can affect dramatically recognition performance [15]. Besides the variations of lighting conditions and pose, face images may suffer from additional factors such as face expression, changes in hair style, cosmetics and aging. Changes in illumination is the most difficult problem in face recognition [1]. The presence of disturbing factors requires different sophisticated methods for face verification and face identification.

This work is motivated by the fact that face verification becomes a complex problem with the presence of disturbing factors. To deal with this issue, different techniques and methods are to be applied and analyzed so that suitable methods for matching of images under different conditions can be found out.

The main goal is to match two face images, FOI and TFI, in the presence of noise, illumination variations, scaling, rotation and translation. Similarity values obtained from the matching process will be analyzed to understand how the face verification can be done in the presence of disturbing factors. Even though it is important to analyze and understand all these factors in a face verification process, in this work, as a preliminary study, experiments are done using artificially generated images. It is important to mention that just one specific technique may not be able to cope with all issues previously mentioned. Hence, this paper focuses on two traditional techniques, template matching (TM) based

on cross-correlation, and histogram matching (HM), applied to the recognition of face images under different conditions.

The remaining of the paper is organized as follows: In Sections 2 and 3, relevant information and related works on TM and color histograms are exposed. In Section 4, we explain how the images were prepared using an image processing application adding RGB noise, Gaussian blur and other image variations. Experiments and results are shown in Section 5 and, finally, Section 6 outlines some conclusions.

## 2. Template Matching

Template matching based methods have been widely used in the image processing field, since templates are the most obvious mechanism to perform the conversion of spatially structured images into symbolic representations [11]. Examples of application areas include object recognition and face recognition or verification. The main objective in this case is to determine whether two templates are similar or not, based on a measure that defines the degree of similarity.

A major problem of this technique is related to the constraints associated to templates. Comparing the representations of two similar shapes may not guarantee a good similarity measure if they have gone through some geometric transformation such as rotation or variation in lighting conditions [15].

TM based techniques have also been applied to face localization and detection, since they are able to deal with interclass variation problems related to the differences between two face images [3]. In summary, face recognition using TM consists on the comparison between bi-dimensional arrays of intensity values corresponding to different face templates. In other words, TM basically performs a cross-correlation between the stored images and an input template image, which can be in grayscale or in color. In this scheme, faces are normally represented as a set of distinctive templates. Guo and colleagues [6] built abstract templates for feature detection in a face image, in contrast to traditional template matching approaches in which fixed features of color or gradient information are generally used.

Recently, several works that combine different features or methods to detect faces have been proposed. For instance, the work presented by Jin and colleagues [8], in which a face detection method that takes into account both skin-color information using TM was proposed. Similarly, Sao and Yegnarayana [13] proposed a face verification method addressing pose and illumination problems using TM. In that work, TM is performed using face images represented by edge gradient values. Predefined templates – represented by objects such as eyes, nose or the whole face – that repre-

sent the features of target face images are used to find similar images [6].

Although TM has been widely applied to face recognition systems, it is highly sensitive to environment, size, and pose variations. Hence, reliable decisions can not be taken based on this approach and other approaches should be studied to improve the performance of the face verification process. Besides TM, histogram matching is also one of the traditional techniques used to compare images [12] and will be explored in the next section.

## 3. Color Histograms

Color is an expressive visual feature that has been extensively used in image retrieval and search processes. Color histograms are among the most frequently used color descriptors that represent color distribution in an image. Histograms are useful tools for color image analysis and the basis for many spatial domain processing techniques [5]. Since histograms do not consider the spatial relationship of image pixels, they are invariant to rotation and translation. Additionally, color histograms are robust against occlusion and changes in camera viewpoint [12].

A color histogram is a vector in which each element represents the number of pixels of a given color in the image. Construction of histograms is basically done by mapping the image colors into a discrete color space containing  $n$  colors. It is usual to represent histograms using the RGB (Red, Green, Blue) color space [12]. For the same purpose, other color spaces such as HSV (Hue, Saturation, Value) and YCbCr (Luma, Chroma Blue, Chroma Red) can also be calculated by linear or non-linear transformations of the RGB color space [9]. It is relevant to mention that color descriptors originating from histogram analysis have played a central role in the development of visual descriptors in the MPEG-7 standard [10]. Though histograms are proven to be effective for small databases due to their discriminating power of color distribution in images, they may not work for large databases. This may happen because histograms represent the overall color distribution in images and it is possible to have very different images with very similar histograms.

Even though histograms are invariant to rotation and translation, they can not deal effectively with illumination variations. Several approaches have been proposed to deal with this issue. An important approach in this direction was proposed by Finlayson and colleagues [4], in which three color indexing angles are calculated using color features to retrieve images. Jia and colleagues [7] have compared different illumination-insensitive image matching algorithms in terms of speed and matching rates on car registration number plate images. In that study, the color edge co-occurrence histogram method was found to be the best

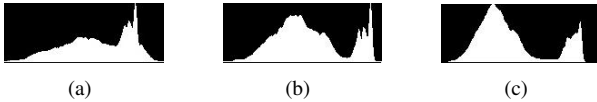
one when both speed and matching performance were considered.

#### 4. Image Preparation

The main objective of this work is to analyze the similarity between one FOI and several TFIs under different conditions using TM and HM. The face object image that was used in this work is shown in Figure 1 and its corresponding color histograms (red, green and blue channels) are shown in Figure 2. This image was acquired under illumination controlled condition and was artificially manipulated using an image processing application to generate several TFIs. The image variations introduced are divided into the following categories: RGB noise, Gaussian blur, changes in lighting, planar translation, rotation and scaling. Increasing levels of Gaussian blur was applied to the FOI. Likewise, more TFIs were generated with added RGB noise. In the case of translation, the FOI was manipulated by gradually displacing it in horizontal and vertical directions by two pixels for each target face image, independently – four images were created for translations in each direction. In the same way, rotated images were generated in both clockwise and counterclockwise directions, varying from -20 to +20 degrees in increments of 5 degrees. Finally, the FOI was submitted to scaling from 70% to 130% of its original size. Some samples of noisy images, as well as rotated and translated images are shown in the next section.



**Figure 1. Face object image used in the experiments.**



**Figure 2. Color histograms of the used face object image: red (a), green (b), blue (c).**

#### 5. Experiments and Results

All experiments were conducted in a Linux platform using implementations in C language using the OpenCV library [2]. The FOI was matched to all TFIs in each category of disturbed images. In each experiment, TM was performed first and then, histograms were constructed to determine the similarity between two images. In the case of histograms, three individual histograms per color channel (Red, Green and Blue) are constructed. Similarity values were calculated by comparing the FOI and TFI. Through TM, similarity values were calculated using the sum of absolute differences of pixel values of the two images and when using HM similarity values were calculated using the correlation method [2]. In this section, result data, figures and graphs obtained from experiments are presented. Some sample images with variations are shown in Figure 3.



**Figure 3. Sample target face images with RGB noise (a), Gaussian blur (b) and illumination variation (c).**

The similarity values obtained using images with Gaussian blur are shown in Table 1. According to these values, it can be observed that slight variations caused in images by applying Gaussian blur did not produce any significant changes. Both TM and HM have produced approximately the same results.

Blur Level	TM	Histogram
5%	0.9923	0.9984
8%	0.9899	0.9979
11%	0.9880	0.9970
14%	0.9864	0.9965
17%	0.9851	0.9953
21%	0.9834	0.9940
24%	0.9823	0.9929

**Table 1. Similarity values of face images with Gaussian blur.**

The experiment based on the addition of RGB noise shows that a gradual increase of noise (from 10 to 40%) reduces the similarity values in the same order of the noise level. However, similarity values obtained by HM are lower than the ones obtained by TM. As the noise level increases, the variation of similarity between TM and HM also increases gradually from 2% to 8%. These experimental results are shown in Table 2.

Noise Level	TM	Histogram
10%	0.9750	0.9544
15%	0.9623	0.9265
20%	0.9496	0.9015
25%	0.9370	0.8795
30%	0.9246	0.8606
35%	0.9125	0.8436
40%	0.8789	0.7823

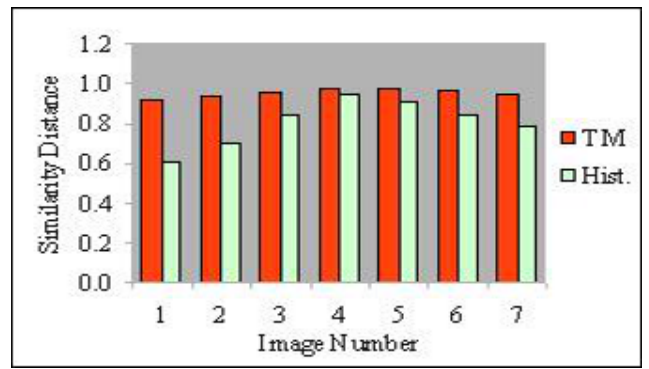
**Table 2. Similarity values of face images with RGB noise.**

Similarity values of images under different lighting condition differs from other disturbing factors such as Gaussian blur or RGB noise, as shown in Table 3 and Figure 4. In this experiment, the histogram similarity values vary significantly when compared to TM similarity values. It is important to mention here that the target face images were created with slight artificial variations of lighting.

Image No.	TM	Histogram
1	0.9166	0.6133
2	0.9373	0.7020
3	0.9578	0.8423
4	0.9769	0.9524
5	0.9845	0.9056
6	0.9732	0.8445
7	0.9536	0.7852

**Table 3. Similarity values of face images with different lighting conditions.**

Results shown in Table 4 show that similarity values decrease with changes in image size. For the target face image with 0% scaling, since it is the same as the FOI, similarity reaches the maximum level. The similarity measure decreases in both scaling directions (image set -30%, -20%, and -10% and image set +10%, +20% and +30%). In this experiment, HM produced better results than TM. Average



**Figure 4. Comparison of face images with illumination variation (lighting level increases from image 1 to 7).**

variation of similarity values between the two methods was about 3%.

Scale	TM	Histogram
-30%	0.8534	0.8572
-20%	0.8695	0.8970
-10%	0.9095	0.9510
0%	1.0000	1.0000
+10%	0.9139	0.9561
+20%	0.8811	0.9131
+30%	0.8619	0.8834

**Table 4. Similarity values of scaled face images.**

As happened with scaled images, rotated images also presented similar results, which are shown in Table 5. Figure 5 shows sample TFIs in which the angle varied from -20 degrees to +20 degrees, i.e. image rotation was performed both in clockwise (positive) and counterclockwise (negative) directions. The image with 0 degree rotation again represents the original face object image. As happened with scaled images, the performance of HM is much better than TM, as expected, because HM is invariant to rotation.

In the experiments regarding planar translation, HM results are better than TM results, as shown in Table 6. The average variation in similarity values between both methods is about 2.6%, but the difference in similarity values increases gradually as the translation increases in both directions when compared to the original FOI. Figure 6 shows sample translated images.

Rotation in degrees	Image	TM	Histogram
-20	Figure 5(a)	0.8893	0.9750
-10	Figure 5(b)	0.9235	0.9935
-5	Figure 5(c)	0.9455	0.9975
0	Figure 1	1.0000	1.0000
+5	Figure 5(d)	0.9506	0.9992
+10	Figure 5(e)	0.9243	0.9945
+20	Figure 5(f)	0.8847	0.9574

**Table 5. Similarity values of rotated face images.**

Translation in pixels	TM	Histogram	Variation in Similarity
6 (X)	0.9598	0.9913	3.3%
4 (X)	0.9677	0.9963	3.0%
2 (X)	0.9760	0.9965	2.1%
0	1.0000	1.0000	0.0%
2 (Y)	0.9790	0.9992	2.1%
4 (Y)	0.9662	0.9966	3.1%
6 (Y)	0.9565	0.9879	3.3%

**Table 6. Similarity values of translated face images (X and Y directions).**



**Figure 5. Sample rotated images.**

A global assessment of all experiments is shown in Table 7, where it can be seen that for images that involve geometric transformations, HM is the best method, and it is also suitable for images with Gaussian blur. Since the average variation in similarity values between HM and TM for Gaussian blur is about 1.0%, it can roughly be concluded that both methods are suitable for this disturbing factor. The previous conclusion regarding HM confirms that histograms are invariant to rotation and translation, as mentioned in Section 3. At the same time, TM produces the best performance when dealing with RGB noise and different lighting conditions. As shown in Table 7, the average variation of similarity values is most significant for changes in lighting conditions when compared to other image variations. Figures 7 and 8 summarize the brief discussion in this section. These graphs were plotted using the variation in similarity values between TM and HM for each image – the graph in Figure 7 regards images with added noise and changes in lighting, and the graph in Figure 8 regards images with ge-



**Figure 6. Sample translated images in X and Y directions (shown by dark lines).**

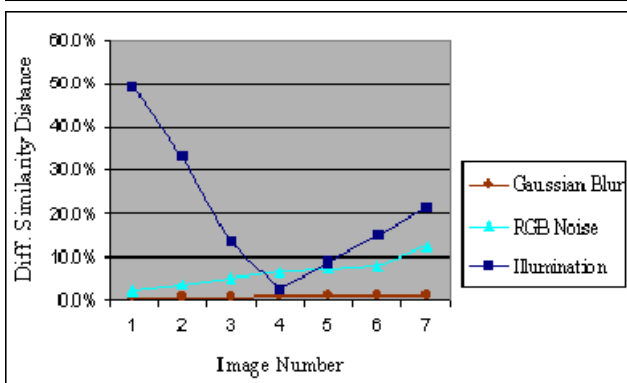
ometric transformations. From these graphs, it can be easily seen that different lighting conditions and rotation result in significant similarity variations between TM and HM.

Image Variation	Best Method	Average Variation in Similarity
Gaussian blur	Histogram	1.0%
RGB noise	TM	6.5%
Lighting	TM	20.7%
Scaling	Histogram	2.7%
Rotation	Histogram	6.2%
Translation	Histogram	2.4%

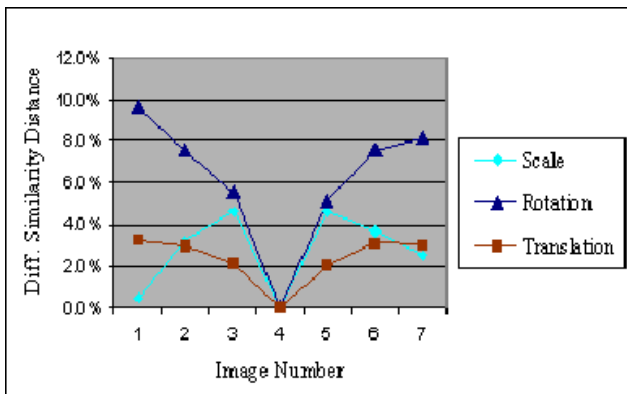
**Table 7. Performance comparison.**

## 6. Conclusion

In this work, TM based on cross-correlation and histograms were used to compare face images. In real-world applications, images may have variations due to noise, lighting conditions, scaling, rotation and translation. To understand and analyze the influence of image variations in the face verification process, TM and HM methods were compared. Both methods are dependent on the value of im-



**Figure 7. Variation in similarity values between TM and histogram for Gaussian blur, RGB noise and illumination variation.**



**Figure 8. Variation in similarity values between TM and histogram for scaling, rotation and translation.**

age pixels – TM depends on the local pixel information, mean HM on the global pixel information of the face images. According to the comparison of methods applied to the face object image and different target face images used in this work, TM can be considered as a suitable method for images with RGB noise, Gaussian blur and images with slight variations in lighting conditions, and HM for face images under different geometric transformations. As a general conclusion, it can be pointed out that images with changes in illumination require more investigation so that the most suitable matching method for face verification can be determined. In this work, global histograms of the RGB color channels were analyzed for face verification. Although global histograms capture and represent the image

color distribution and are suitable for face recognition and related tasks, when dealing with image influenced by disturbing factors more investigation using local image information is needed.

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