Facial expression and lighting conditions influence on face recognition performance

Miloš Pavlović, Ranko Petrović, Branka Stojanović and Srđan Stanković

Abstract— **Face recognition is one of the biometric methods which have found practical uses for different purposes. Visible light face recognition systems have been well developed and achieve very good performance in controlled conditions. This paper compares the effect of different facial expressions and different illumination on face recognition performance with the face recognition code based on Histogram of Oriented Gradient (HOG) features extract method. The results presented in this paper points to the fact that different illumination conditions have significant impact on facial recognition systems performance, and that a new sensor based on infrared imaging should be included.**

Index Terms— **Face recognition, facial expression, illumination, HOG features, Support Vector Machine .**

I. Introduction

Face is a specific characteristic of every human person. Facial lines help us to recognize our acquaintances and distinguish them from unknown people. The human brain is fairly well in recognizing faces and able to make the right decision even in difficult conditions such as poor lighting, aging of the face, wearing glasses or changing the hairstyle. That is the goal that we want to achieve with face recognition systems. In recent years considerable progress has been made on the problems of face detection and recognition. Face recognition systems are used to identify faces in photos within social networks, control access to various places, as well as in surveillance systems. The goal of any face recognition system is to find and learn features that are special among people. In controlled conditions, without external disturbances and facial expression changes, modern systems for face-to-face identification have good performance. However, the problem of face recognition from a general view point remains largely unsolved, because transformations, such as orientation, position, facial expression and illumination, cause the face's appearance to vary substantially. This is the problem which prevents the existing algorithms from reaching their maximum accuracy.

The goal of this paper is to determine how much facial expressions and different lighting conditions have influence on recognition performance in the existing systems[1]. This paper proposes an environment for testing performance in a variety of conditions consisting of databases with images of different facial expressions (smiley, boring and faces with open mouth) and different illuminations (faces in daylight, with additional frontal light source and faces in darkness) and a system for classification based on Histogram of Oriented Gradients (HOG) [2][3] features descriptor and Support Vector Machines (SVM) classifier [4][5].

The paper is organized as follows. Section II describes the face recognition algorithm including HOG features and SVM classifier and the original image database. Section III describes the developed test environment for different facial expressions, illuminations and evaluation methodologies. Section IV presents a statistical and visual comparison of the tested algorithms. The Section V lists conclusions and future work in this research area.

II. System Descriptions

A. Face recognition algorithm

The goal of a face recognition system [6] is to find and learn features that are characteristic among people. While it is important to learn characteristic features, it is also important to minimize differences between faces of a same person captured in different conditions. A face recognition system is based on local and global features of the face that are discriminative under controlled environment. Pose robust algorithms use common subspace learning in which the features of different faces are transformed into a subspace where the inter class variations are maximized and intra-class variations minimized allowing better classification of the facial images. Fig. 1 shows a block diagram of a face recognition system which computes distinctive features and learns them for recognition. As a feature descriptor this paper uses the Histogram of Oriented Gradients - HOG descriptor [2] [3] and the Support Vector Machines (SVM) [4] [5] for classifier.

Support Vector Machines is a specific method of supervised machine learning to determine the boundaries of the decision-making region of a linear classifier or solving the regression problems of estimating the value of functions,

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derived from the statistical theory of learning. It is based on the concept of direct learning based on the data collected in a high-dimensional space of features, without the need for knowing or estimating any probability density function. The SVM model is a representation of the features as points in space, mapped in such a way that the features of different classes are separated by classification gap that is as wide as possible. SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space, that is used for classification. Separation is realized by the hyperplane that has the largest distance to the nearest training-data point of any class, called functional margin, since in general the larger the margin produces the lower error of the classifier. The hyperplanes present the set of points in the higher-dimensional space which have constant dot product with a vector in that space. The vectors determining the hyperplanes are chosen to be linear combinations with parameters α_i of images of feature vectors x_i that occur in the face database. This choice of a hyperplane, the points $\boldsymbol{x}$ in the feature space that are mapped into the hyperplane are defined by the relation:

$$\sum_i \alpha_i k(x_i, x) = consant \tag{1}$$

SVM uses mappings that are designed to provide easy computation of dot product in terms of the variables in the original space by defining them in terms of a kernel function $k(x_i, x)$ selected to adapt to the problem. The sum (1) is used for measuring the relative distance of each test point to the data points from the sets to be discriminated, because $k(x, y)$ becomes small as absolute difference of x and y becomes greater, each term in the sum measures the degree of nearness of the test point x to the matching database point x_i. As a reference classifier for comparison of performance we have used *fitcecoc* - SVM implemented in Matlab [7]. Selection of SVM is justified by the fact that high dimensional the HOG feature vector has been used, eliminating the need for additional non-linear mapping into a larger space that would corresponds to non-linear SVM.

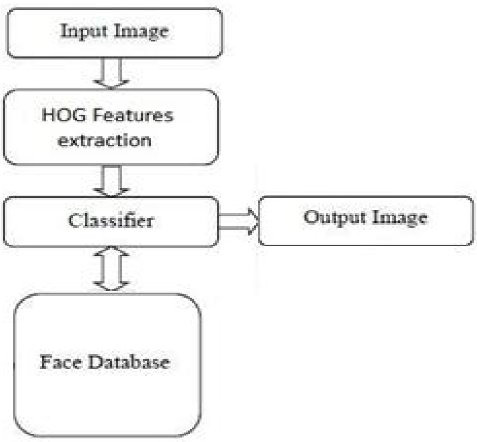

Fig. 1. Block Diagram of Face Recognition System

The issue of choosing, preparing and getting good features is crucial for determination the overall performance of the detection system. Histogram of oriented gradients is the vector composed of a certain number of discrete histograms of the gradient values obtained by processing images over cells within a window and normalizing blocks of more than one cell. The gradient in digital image processing represents a generalization of the gradient operator on a discrete image signal and a vector indicating the direction and direction of the highest increase in illumination in each pixel. Therefore, first it is necessary to discretize possible values of gradient directions, and then their counting by cells. After defining the allowed directions that a gradient can occupy in each pixel, the gradient has to be projected on two closest, neighboring directions. The projection implies redistribution of the value of the gradient module to the allowed, discrete directions in the ratio that corresponds to the angular distance of the gradient from each of them; more precisely the interpolation of the gradient value is performed. Histogram values describe the presence of dominant directions in the observed cell, and in this way, locally, the presence of edges in the image for multiple adjacent cells. The resulting histograms, in the case of one image from the base, are shown graphically in Fig. 2.

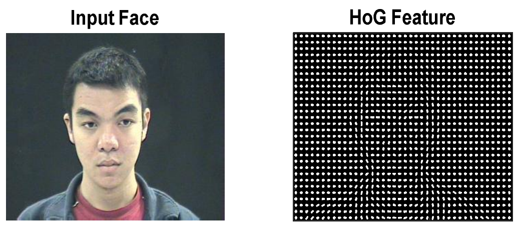

Fig. 2. Face with HOG features

B. *Facial image database*

The dataset used in this study was generously provided by the authors of [8]. The database contains color and thermal images of 29 people under different lighting conditions and with different facial expressions. For each person in database there are 3 subsets with 11 color and 11 thermal images captured from different angles with smiling, boring and open mouth facial expressions, as well as 5 subsets with 11 color and 11 thermal images under different illumination: daylight, three different light sources (frontal, left lateral and right lateral) and faces in the darkness. All the images in database have the same orientation and the same dimensions, which do not require additional preprocessing in that sense. Fig. 3 shows all faces in database.

Fig. 3. Different faces in database

III. EXPERIMENTAL WORK

Algorithm performance for different facial expressions (shown in Fig. 4) has been tested on four sets of images. For each person from database we have used two different images per test set for each facial expression. All images in the test sets are frontally oriented to see exclusively the influence of different expressions on the algorithm performance. The first set consists of images with "neutral" facial expression, second with boring faces, the third with smiling faces and in the fourth set of pictures are faces with open mouth.

Fig. 4. Different facial expression (from left to right: neutral, smiley, boring and open mouth)

For different lighting conditions the algorithm was tested on three sets of images - Fig. 4. The first set contains images of faces with frontal light source, the second faces without additional illumination (on daylight), and the third images of faces in the dark. For each person from database, we have used two different images per test set for each illumination. Also, in the test sets, all images are frontally oriented to see exclusively the influence of different lighting conditions on the algorithm performance.

Fig. 5. Different illumination (from left to right: daylight, additional light and darkness)

A. *Evaluation methodology*

The diagnostic ability of a classifier system when its discrimination threshold is varied is graphically plotted as a Receiver Operating Characteristic curve - ROC curve [9]. Accuracy of classification system is measured by the area under the ROC curve [10], where greater area means a more useful test. The ROC space is defined by True Positive Rate (*sensitivity*) - the number of well recognized faces and False Positive Rate (*1-specificity*) - the number of wrong recognized faces - "false alarm". Each point on the ROC curve represents sensitivity pair corresponding to a particular decision threshold.

The performance statistics are also presented as cumulative match scores - CMC curves [11]. The rank is plotted on the horizontal axis and runs from rank 1 up through the number of faces in database. The vertical axis is the percentage of recognition accuracy at that rank. We calculated scores to evaluate the algorithm performance on different categories of test sets - different facial expressions and different illuminations. For each probe face, there is a corresponding database face of the same person. In order to generate a CMC curve, the base is sorted by decreasing similarity for each probe face, and the probe face is said to be correctly recognized at rank *r* if the database face of the same person is among the first *r* faces in the sorted database. The most important performance indicator is the recognition accuracy on rank 1.

IV. RESULTS AND DISCUSSION

Algorithm performance on different facial expression is shown with ROC curves - Fig. 6, and CMC curves - Fig. 7.

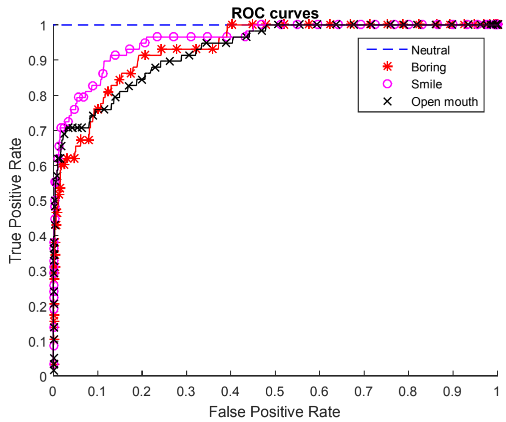

Fig. 6. - ROC curves for different facial expression

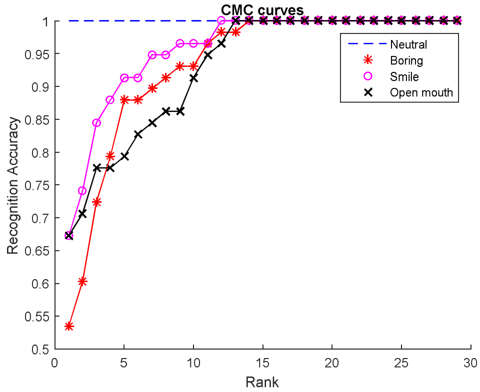

Fig. 7. CMC curves for different facial expression

The attached graphics of CMC and ROC curves shows that the system works very well for people with "neutral" facial expression, which is expected, as the persons from this test set have the closest facial expression to those who are in the base. Lower accuracy is obtained for smiling faces and faces with open mouth. For these two facial expressions, the results are quite similar, because the faces at these images have changes in the same part of the face (around the mouth) relative to the images in the database, i.e. this is the area where pixels have changed, which affects the gradient of brightness and HOG features of that part of face. For the bored look of the face, the whole surface of the face has changes in appearance compared to the "neutral" facial expression, and, therefore, also the pixels on this test images have changes in a much wider range compared to those in the images in database, which results in worse recognition.

TABLE 1 shows area under the ROC curve (AUC) and Rank 1 accuracy, as the most important indicators of algorithm performance for different facial expressions. The presented results support the conclusions drawn from ROC and CMC curves.

TABLE 1
AUC AND RANK-1 ACCURACY FOR DIFFERENT FACIAL EXPRESSION

	Neutral	Boring	Smile	Open mouth
AUC	1	0.92	0.95	0.91
Rank 1	1	0.53	0.67	0.67

Algorithm performances on test sets with different illumination conditions are shown by ROC curves - Fig. 8, and CMC curves - Fig. 9.

Graphics of CMC and ROC curves show that the recognition is exceptionally good for images of faces without additional illumination (on daylight), what is expected, because the lighting conditions on images from this test set are the most similar to those in the database. A little lower accuracy is obtained for images of faces with an additional frontal light source. This is also an expected result, as all facial features are visible in this test set of images and the gradient of brightness is quite similar to the images in base. Very bad results have been obtained for faces in the darkness. In these images, faces are poorly noticeable; the gradient of brightness is significantly different from the images in database, which results in huge mistake in recognition.

TABLE 2 shows the area under the ROC curve (AUC) and Rank 1 - accuracy, as the most important indicators of the algorithm performance for different illuminations. Presented results supports the conclusions drawn from ROC and CMC curves.

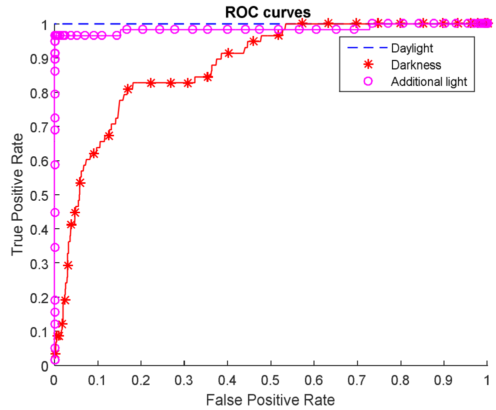

Fig. 8. ROC curves for different illumination

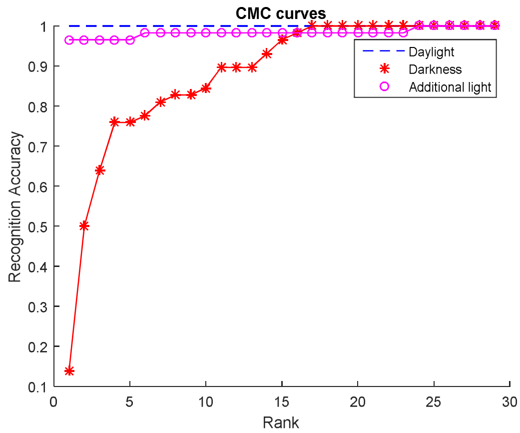

Fig. 9. CMC curves for different illumination

TABLE 2
AUC AND RANK-1 ACCURACY FOR DIFFERENT ILLUMINATION

	Daylight	Darkness	Additional light
AUC	1	0.86	0.98
Rank 1	1	0.13	0.96

V. CONCLUSION

In this paper it has been shown that the tested face recognition algorithm works very well, with exceptional performance, for images captured in controlled conditions, such as images in personal documents. However, changes in certain parts of the face, such as area around mouth, lead to a significant degradation in the performance of the algorithm. Lighting conditions have a major impact on face recognition system performance, what is particularly evident in low light conditions. This system completely fails in darkness and as an option for further improvement we suggest using thermal infrared face recognition. This type of system as a new model for face recognition has been described in the literature [12]. Infrared systems are less dependent on the angle and brightness of the light, adaptive on different light conditions and is absolutely applicable in conditions of complete darkness. Such systems will be a part of our future research.

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