Histograms of Gabor Ordinal Measures for Face Representation and Recognition

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Abstract

This paper proposes a new image representation method named Histograms of Gabor Ordinal Measures (HOGOM) for robust face recognition. First, a novel texture descriptor, Gabor Ordinal Measures (GOM), is developed to inherit the advantages from Gabor features and Ordinal Measures. GOM applies Gabor filters of different orientations and scales on the face image and then computes Ordinal Measures over each Gabor magnitude response. Second, in order to obtain an effective and compact representation, the binary values of each GOM, for different orientations at a given scale, are encoded into a single decimal number and then spatial histograms of non-overlapping rectangular regions are computed. Finally, a nearest-neighbor classifier with the χ^2 dissimilarity measure is used for classification. HOGOM has three principal advantages: 1) it succeeds the spatial locality and orientation selectivity from Gabor features; 2) the adopted region-comparison strategy makes it more robust; 3) by applying the binary codification and computing spatial histograms, it becomes more stable and efficient. Extensive experiments on the large-scale FERET database and AR database show the robustness of the proposed descriptor, achieving the state of the art.

1. Introduction

Face recognition is a hot topic due to its wide applications such as access control, human-computer interaction, teleconference and visual surveillance [4]. It has received much attention during last decades. However, variations such as illumination, pose, aging, occlusion and expression, make it still challenging. How to represent a face in a proper way is very important to deal with those variations in the face recognition process. The main methods to represent face images can be divided into two categories [4, 20]: subspace based holistic methods and local appearance based methods. Holistic appearance based methods such as PCA, LDA, ICA perform well when all conditions are under control, moreover they usually need a large and representative training set to obtain a better performance [17]. On the other hand, local appearance based methods have shown better results when dealing with different face variations and they are more appropriate when having only one image per person for training, which is usual on real applications [1, 3, 14].

Local methods based on Gabor wavelets have been ones of the most successful in face recognition [5, 10]. Gabor wavelets encode the local structure of the image for a specific frequency and orientation meanwhile preserving the spatial relations of the facial shape. The magnitude values of Gabor responses are rich in texture, suitable for describing the face structure; but at the same time, for each selected orientation and spatial frequency, they present slowly variations with the spatial position, so they can be further encoded with a local method looking for a more efficient representation [18, 19]. In recent works, the Local Binary Pattern (LBP), which has shown to be also a powerful local texture descriptor [1], has been applied to the Gabor responses to obtain a more robust face descriptor [6, 19]. By combining these two face descriptors better results have been reported on different situations [6, 19]. However some of the proposed descriptors are highly dimensional or required a statistical learning procedure.

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In [13] it has been stated that LBP could be treated to some extent as a special case of Ordinal Measures. Ordinal features can represent local structures of different complexities in images by encoding the qualitative relationship between different regions [7, 12]. Motivated by this, we propose to exploit Gabor features together with Ordinal Measures and give a very simple scheme for fusion. Ordinal Measures are used after applying Gabor filters to the face image. The obtained binary values are encoded into a more compact representation. Moreover, taking into account that obtained features are mainly texture descriptors, we make use of spatial histograms to model them more efficiently.

The reminder of this paper is organized as follows: In Section 2 we describe in details the novel Histograms of Gabor Ordinal Measures (HOGOM) method. Section 3 presents how to conduct the face recognition process using the weighted HOGOM features. Section 4 will give the results of the proposed method in comparison with some classical algorithms on two face databases. Finally, conclusions and future work will be stated.

2. Face Description and Recognition using HOGOM

The steps of the new HOGOM representation are summarized in Figure 1 and will be described in details in the following subsections.

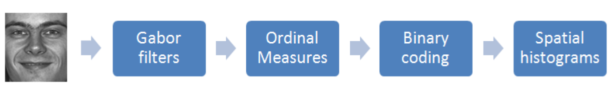

Figure 1. Steps for obtaining the HOGOM face representation

2.1. Gabor Magnitude Images

The family of 2D Gabor filters composed by five frequencies and eight orientations usually used for face recognition [10], can be formulated as [5]:

$$\psi_{\mu,\nu}(z) = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{\left(-\frac{\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}\right)} \left[e^{ik_{\mu\nu}z} - e^{-\frac{\sigma^2}{2}}\right] \tag{1}$$

where $\mu \in \{0, ..., 7\}$ and $\nu \in \{0, ..., 4\}$ determine the orientation and scale of the Gabor filters and $z = (x, y)$ represents the spatial position. The wave vector $k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$ has a magnitude $k_\nu = k_{\text{max}}/\lambda^\nu$, where λ is the frequency ratio between filters and $\phi_\mu = \pi\mu/8$.

The response of an image $I(x, y)$ to a wavelet $\psi_{\mu,\nu}(z)$ is obtained by the convolution:

$$G_{\mu,\nu}(x, y) = I(x, y) * \psi_{\mu,\nu}(z). \tag{2}$$

The Gabor wavelet coefficient obtained for a given scale and orientation in Equation (2), is a complex number which can be expressed as [10]:

$$G_{\mu,\nu}(x, y) = A_{\mu,\nu}(x, y) \cdot e^{i\theta(x,y)} \tag{3}$$

where A represents the magnitude and θ the phase.

It has been seen that the magnitude varies slowly, while the phase information varies its rotation with the spatial position [19, 18]. For this reason, only the magnitude is usually used for face classification [10, 6, 19]. For a given image, the magnitude values computed for every pixel at a given orientation and scale, conform a "Gabor Magnitude Image" with the same dimensions of the original image. It means that 40 Gabor Magnitude Images are obtained for a face image by using five scales and eight orientations Gabor filter bank.

2.2. Gabor Ordinal Measure features

Good results have been obtained in face recognition by encoding Gabor responses with the Local Binary Patterns (LBP) method [6, 19]. The original LBP operator is a texture descriptor which represents the local microstructures of an image by comparing every pixel with its 3x3 neighborhood pixels [1]. In each comparison it is only considered whether the pixel value is bigger or smaller than the center pixel value, so it can be said that the LBP code models the ordinal relationships between one pixel and its neighborhood [13].

Ordinal Measures (OM) are a kind of simple concept, which just compare two different regions (e.g. region A and region B) to see which one has a larger value. If A has a larger value than B, thus the code is 1, otherwise 0. OM descriptors can represent different local structures on images. They encode the qualitative relationship between different regions.

Using a bit-wise comparison in a small neighborhood is not possible to capture larger scales structures, while comparing neighborhood regions at different scales, macrostructures of different complexity can be represented. Moreover the region based comparison is less affected by noise than the LBP coding strategy, where a number of pixel based comparisons are performed in a small neighborhood. It means that region-comparison strategy makes the descriptor more stable.

OM were firstly used in [11] as face image descriptors and demonstrated to be robust to different illuminations and sensor noise on face detection. In [7] promising results were obtained using OM for face recognition. In this case a statistical learning procedure was used. Good results were also achieved on iris recognition task by combining different kinds of Ordinal features [12].

Trying to avoid the use of the statistical learning techniques and considering the robustness of Gabor features to model the intra and extra person variations, we propose to insert a Gabor filtering process before using the OM. In this way, we encode the Gabor Magnitude Images by using OM in order to get a more stable representation.

In Figure 2, one ordinal filter is applied directly to four face images (two images of two persons), and is compared with the same ordinal filter applied after a Gabor filtering. The first row in the figure shows original images. Note that the two images of every person have different expressions. The second row shows the four images obtained by applying one ordinal filter to each one of the original images, without applying Gabor filters as a primary step. Finally, in the third row, the four Gabor Ordinal Measures (GOM) filtered images are shown. It can be seen that the GOM images show less differences for the same person and more differences for different persons. Moreover, we calculated the intra and inter class differences for both cases by using Hamming distances, and found that the intra difference for OM directly was 0.211, even larger than the 0.202 obtained for its inter difference, while for GOM the intra difference was 0.186, much smaller than the inter difference, 0.295.

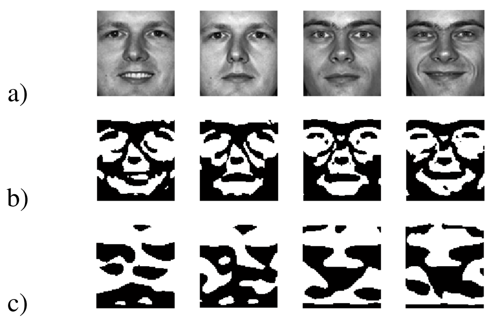

Figure 2. Comparison between b) Ordinal Measures and c) Gabor Ordinal Measures obtained from a) two images of two different persons.

In this paper, we aim to demonstrate the strength of combining Gabor features with OM, meanwhile avoiding the curse of dimensionality, so only the four simplest ordinal filters are employed (see Figure 3). In this way, the feature dimension will be four times the dimension of Gabor features. Experimental results demonstrate that this even simple setting of OM can help the proposed method to achieve a promising result.

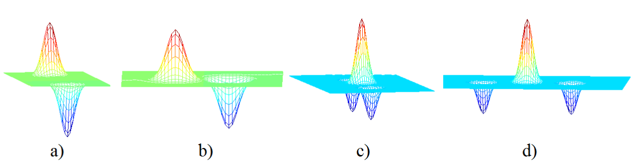

Figure 3. Four ordinal filters used in this paper: a) two lobes vertical, b) two lobes horizontal, c) three lobes vertical , d) three lobes horizontal.

2.3. Binary Coding of Gabor Ordinal Measures

After applying the ordinal filters over Gabor responses, a set of 40 features with the same dimensions of the original image is obtained for each Ordinal Measure. In order to represent those features in a compact way, the ordinal codes for each pixel at different orientations can be concatenated for a given scale:

$$BGOM_{\nu}^{i}(x,y) = [GOM_{0,\nu}^{i}(x,y), GOM_{1,\nu}^{i}(x,y), \\ ..., GOM_{7,\nu}^{i}(x,y)] \tag{4}$$

where $BGOM_{\nu}^{i}(x,y)$ is the codification obtained at position (x,y) for the i-th ordinal measure at ν scale.

Since the ordinal codes are binary values and eight orientations are used, we will obtain a binary number of 8 bits, which can be converted to a decimal number (a byte) for representing each pixel at each scale:

$$BGOM_{\nu}^{i}(x,y) = GOM_{0,\nu}^{i}(x,y) * 2^{7} \\ + GOM_{1,\nu}^{i}(x,y) * 2^{6} + ... + GOM_{7,\nu}^{i}(x,y)] \tag{5}$$

By using this encoding, we obtain a single representation for every ordinal feature at each scale. In Figure 4, a codified GOM for a given scale is visualized as a gray-level image. Images in the left correspond to the eight orientations that were encoded into one.

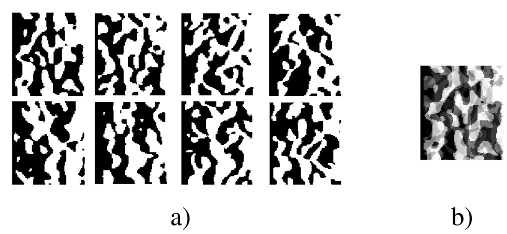

Figure 4. Representation of the GOM encoding process. a) Images obtained for an Ordinal Measure at eight orientations for a given scale. b) Codified GOM obtained from images in (a).

2.4. Histograms of Gabor Ordinal Measures

Looking at Figure 4 (b), we observed that the image has a rich texture. Histograms are a very good tool for describing texture patterns [18, 19]. Since a global histogram loses the structure information, we use spatial histograms to capture the spatial relationship between the different regions of the face [1, 19]. Using spatial histograms not only permits to describe the texture, but also can reduce the computational cost in the classification step.

Histograms from non-overlapping regions R_n of each codified GOM, can be obtained as follows:

$$H_{\nu_n}^{i}(l) = \sum_{x,y \in R_n} I\{BGOM_{\nu}^{i}(x,y) = l\}, l = 0,1,...,255 \tag{6}$$

where l represents the l-th grayscale value and $I\{f\} \in \{0, 1\}$ is a boolean indicator of the condition f.

The histogram of each region can be further reduced to be only B bins by partitioning the histograms into uniform parts: $[0, ..., 256/B - 1], [256/B, ..., 2 * 256/B - 1], ..., [(B-1) * 256/B, ..., B * 256/B - 1]$.

Finally, the histograms of the non-overlapping patches computed for each codified GOM can be concatenated together into a higher dimensional histogram or being directly compared using a histogram dissimilarity measure. We use here the χ^2 dissimilarity measure defined as:

$$\chi^2(H1, H2) = \sum_{l=1}^{L} \frac{(H1_l - H2_l)^2}{(H1_l + H2_l)} \tag{7}$$

where $H1$ and $H2$ are the two histograms under comparison and L is the number of bins in each histogram.

Based on Equations (6) and (7) the dissimilarity between the two face images represented by the HOGOM descriptor can be computed as:

$$D(I1, I2) = \sum_{\nu=1}^{F} \sum_{i=1}^{O} \sum_{n=1}^{N} \chi^2(H1^i_{\nu_n}, H2^i_{\nu_n}) \tag{8}$$

where F is the number of scales used in the Gabor filtering, O is the number of ordinal measures used and N is the number of non-overlapping regions in which the image is divided.

3. Weighted Histograms for Robust Face Recognition

It has been shown that different parts of the face have different levels of importance for the subject recognition task [1, 19, 6]. For this reason, when recognizing faces based on regions division, it is usual to set different weights to the features extracted from each part of the image. We can then redefine the computation of the dissimilarity between two face images, considering assigning different weights to the HOGOM descriptor obtained for each block. In this way, Equation (8) can be reformulated as follows:

$$D_\omega(I1, I2) = \sum_{\nu=1}^{F} \sum_{i=1}^{O} \sum_{n=1}^{N} \omega^i_{\nu_n} \chi^2(H1^i_{\nu_n}, H2^i_{\nu_n}) \tag{9}$$

where $\omega^i_{\nu_n}$ represents the weight assigned to the n block of the i-th Ordinal Measure in the ν scale.

Similar to previous works [6, 18, 19], we use the Fisher separation criterion [2] to learn the weights for each block. Given a training set, the weight for a given block under this criterion can be computed as:

$$\omega = \frac{(m_i - m_e)^2}{(\sigma_i^2 + \sigma_e^2)} \tag{10}$$

where m_i and σ_i are respectively the mean and the variance of the intraclass dissimilarity space, and m_e and σ_e are respectively the mean and the variance of the interclass dissimilarity space.

It is important to note that although the weights assignment procedure needs a training set, it does not make any assumption about the statistical distribution of classes for the classification procedure. Hence it does not suffer from the generalizability problem usually present in the statistical learning based classification methods.

The training set of the FERET database was used to compute the weights of each block. Figure 5 shows the weights computed for a set of HOGOMs obtained with one Ordinal Measure at each scale. The obtained weights were scale between 0 and 255 in order to show them as images, in which the darker the color the smaller the weights. It can be seen that regions corresponding to the area of the eyes and the nose are more discriminative.

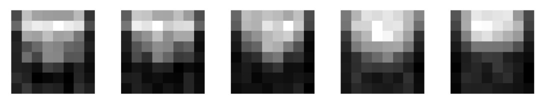

Figure 5. Weights for a set of HOGOM obtained with one Ordinal Measure at five scales.

4. Experimental Evaluation

The FERET [9] and the AR [8] face databases were used to evaluate the performance of the proposed HOGOM face descriptor.

The FERET dataset [9] has been widely used to evaluate different face recognition algorithms. It is divided into five subsets: a gallery set (Fa) is composed by 1196 subjects with one frontal image for each of them, the Fb subset containing 1195 face images with variations in expression; the Fc subset contains 194 images with variations in illumination conditions; the Dup I has 722 face images that were taken with an elapsed time with respect to the images in the gallery set; and the Dup II, a subset of Dup I, contains 234 images in which the elapsed time is at least one year. There is also a training set that is composed of 1002 frontal images. Sample images in each subset are shown on Figure 6. All the images were geometrically normalized to be 128x160 by using the manually located center of the eyes. To obtain the spatial histograms, each image was divided in 8x8 non-overlapped regions, each one of which is with 16x20 pixels of dimension.

On the other hand, the AR database contains more than 3200 face images of 126 people captured on two different sessions. Each session has 13 images per person with variations in expression, illumination conditions and occlusions. In order to compare with previous works [6] we used the same protocol: we randomly selected 90 different subjects (45 male and 45 female), the neutral expression image of every person in each session was used as gallery and the rest of them with different expressions and occlusions were used for testing. The images cropped to 80x88 pixels were used in our experiments. Samples of the used images from one person in one of the sessions are shown on Figure 7. In this case the images were divided into regions of 10x11 pixels of dimension.

For all the experiments we use the histograms reduced to 64 bins as it was explained on Section 2.4, which make the complete process more efficient.

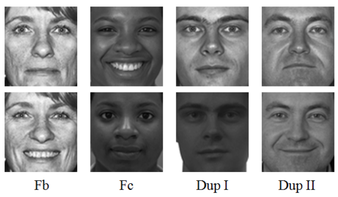

Figure 6. FERET database sample images. The first row shows images in the gallery set and the second row shows some sample images in each one of the other subsets.

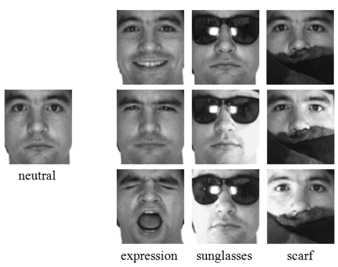

Figure 7. AR database sample images for one subject in one session. Columns show images in each subset.

4.1. Results on the FERET database

In order to quantitatively compare the proposed method with previous works, we consider as a baseline the results reported on FERET [9] and the results reported on other works that also encode the Gabor features with a local descriptor such as the Local Gabor Binary Pattern Histogram Sequence (LGBPHS) [19] and the Histogram of Gabor Phase Patterns (HGPP) [18], more recent works such as the Gabor Volume Based LBP (GV-LBP) [6] and the Patterns of Oriented Edge Magnitudes (POEM) [16] descriptors are also included in the comparison. There are many other face recognition works that have reported their results on FERET database, but most of them use complex classification phase or require a statistical learning procedure. From the selected methods, only GV-LBP [6] uses a learning procedure, but it was chosen because is one of the latest proposals closer to our method.

We perform two tests on the FERET database: in the first one the descriptors are compared directly and in the second one the methods using the weighting process are compared. Results are given in Table 1 and 2. Note that for POEM [16] a weighting process was no considered and the results for GV-LBP [6] without using weights are not reported.

Table 1. Top rank recognition rates on FERET database.

Method	Fb	Fc	DupI	DupII
Baseline [9]	96.0	82.0	59.0	52.0
LGBPHS [19]	94.0	97.0	68.0	53.0
POEM [16]	97.6	96.0	77.8	76.5
HGPP [18]	97.6	98.9	77.7	76.1
HOGOM	98.0	99.5	76.8	78.2
Retina + POEM [16]	98.1	99.0	79.6	79.1
PS [15] + HOGOM	**98.1**	**99.5**	**83.6**	**82.0**

Table 2. Top rank recognition rates on FERET database using weights.

Method	Fb	Fc	DupI	DupII
W-LGBPHS [19]	98.0	97.0	74.0	71.0
W-HGPP [18]	97.5	99.5	79.5	77.8
GV-LBP [6]	98.4	98.9	81.9	81.6
W-HOGOM	99.2	98.9	77.0	80.3
PS [15] + W-HOGOM	**99.2**	**99.5**	**82.7**	**82.1**

For the first experiment, the recognition rates of the five compared methods are tabulated in Table 1. We see that on the Fb and Fc subsets, our HOGOM always achieves the highest recognition rate. Particularly, our HOGOM can significantly outperform LGBPHS on four subsets. Note that both LGBPHS and our HOGOM are based on a further codification of Gabor magnitude responses. This improvement indicates that Ordinal Measures can model the variations of Gabor images more accurately. Therefore the use of HOGOM is recommended to model frontal face and variations incurred by mild expression. We can also observe that even though we only use the four simplest ordinal filters, HOGOM performs just a little worse than POEM and HGPP on the DupI subset, however outperforms them on the DupII, which is a more difficult subset, with a longer elapsed time. This analysis suggests HOGOM is a more stable texture descriptor. Moreover if a preprocessing method is applied better results can be obtained. We repeat the experiment using the preprocessing sequence of Tan and Triggs [15] before applying our HOGOM method and compare the results with the results reported for the POEM method using a preprocessing filter (Retina) [16].

It can be seen on the table the improvement obtained for the HOGOM method, specially for DupI and DupII, achieving the best results.

The second experiment compares the recognition rates by using weighting strategy. On the Fb subset, we see that methods can be ordered in ascending recognition rates as W-LGBPHS, W-HGPP, GV-LBP, W-HOGOM. This result shows that W-HOGOM can deal with frontal faces better than other methods. Comparing Table 1 and 2, we see that the weighting strategy can further improve the recognition rates of HOGOM. Notice that the best results on DupI and DupII are for the best GV-LBP descriptor [6] in which statistical learning techniques are used. For Fc, the best result using weights was obtained by the HGPP method [18], but it was the same obtained by applying HOGOM directly, in which only one image from the subset was misclassified. Using weights we got a second image from this subset misclassified, which was classified on the second position. This behavior could be because there are no images with illumination problems in the training set, so the weights maybe are not suitable for this case. Also for this case the best results are obtained if the preprocessing method is applied.

4.2. Results on the AR database

In order to evaluate the robustness of the proposed HOGOM method in front of occlusions and more drastic expressions we perform an experiment on AR database. Considering that weights can not be suitable for these special cases in which some of the more weighted regions can be occluded, and the results would not reflect the reality for variations that occur in the less weighted regions such as for the scarf occlusion and great mouth expressions, we only make use of direct matching in this case. The comparison results against the results obtained by some of the methods analyzed before, that were reported on [6] under the same protocol, are given in Table 3. In this case, the two versions of the GV-LBP method based on Gabor magnitudes were consider [6]: the GV-LBP on Three Orthogonal Planes (GV-LBP-TOP-M) and the Effective GV-LBP (E-GV-LBP-M).

Table 3. Top rank recognition rates on AR database.

Method	Expression	Sunglasses	Scarf
LBP	87.04	34.63	47.04
LGBPHS	86.11	37.59	82.59
GV-LBP-TOP-M	90.56	53.89	87.41
E-GV-LBP-M	90.93	47.22	82.78
HOGOM	82.77	82.22	95.0

From Table 3 it can be seen that the proposed HOGOM method outperforms significantly the rest of the methods based on LBP, for both sunglasses and scarf occlusions. When there is some occlusion the discriminative information of the face is reduced, however as it was stated before comparing regions instead of pixels can be more effective for representing the remaining face features. Moreover, for the sunglasses case, although the eyes regions are more important for discrimination, when comparing regions instead of pixels, a more stable behavior is exhibited since the eye area and the eyebrows are both dark regions and part of the original information is kept. In this case, a significant improvement from 53.89%, obtained by the best GV-LBP method, to 82.2% was achieved.

For the expression case, we get worse results than all of the LBP-based methods. When analyzing our errors, 97% of them are from the scream expression. The reason of this decreased performance is that we are only using the four simplest ordinal filters, in which all the lobes are fixed at a certain distance, and we are not able to describe all the possible texture variations. Actually, if we use a richer OM set, including lobes distance equal to one pixel like LBP, this problem could probably be solved. In Figure 8 we compare the behavior of one OM when using two different inter lobe distances. We chose one of the 10x11 blocks at the mouth region from two images with very different mouth expressions, and obtained the HOGOM for the vertical two lobes ordinal feature with two different inter lobes distances. The histogram in Figure 8 (c) corresponds to the difference between the HOGOMs of both blocks when using the fixed distance of 7 pixels, while the second one in Figure 8 (d) represents the HOGOMs difference for a smaller distance of 3 pixels. It can be seen that when using a smaller inter lobe distance, the intra difference between both blocks

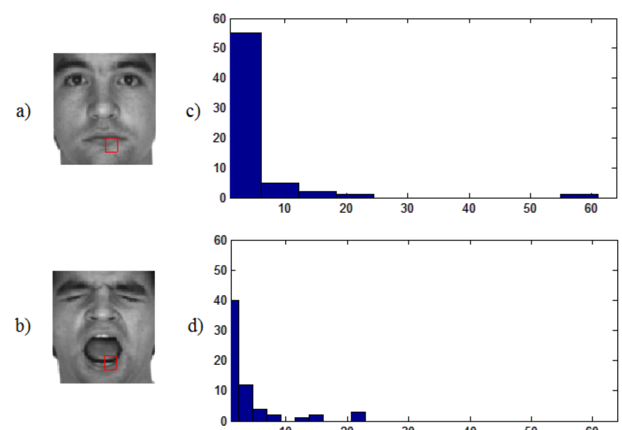

Figure 8. HOGOM comparison for one OM with two different inter lobe distances. a) and b) respectively show the region selected for the comparison in two images from the same person with a neutral expression and a scream expression. c) shows the HOGOMs difference of the two blocks using the vertical two lobes OM with 7 pixels of inter lobe distance. d) shows the HOGOMs difference using the same OM with 3 pixels of inter lobe distance.

can be reduced. In this work we only use four simple OM with fixed inter lobe distances in order to avoid the curse of dimensionality and to explore the benefits of the proposed fusion scheme. Using a more complete OM set [7] would help to improve the obtained results. In that case feature selection or reduction methods need to be used, which is is beyond the scope of this paper. In any case, for the more common expression variations like anger and simile (similar to the ones on FERET Fb subset), the proposed HOGOM performs well with only 3/360 errors.

5. Conclusions and future work

This paper proposes a novel image representation method called HOGOM, which enhances Gabor filters by combining them with Ordinal Measures to extract the discriminative information of face images. The use of a binary encoding makes the representation more compact meanwhile keeps discriminative information. Finally, spatial histograms are used to improve the robustness to external noise. A nearest-neighbor classifier with the χ^2 dissimilarity measure is used for comparing the obtained histograms. The described process does not include a training phase, so generalizability problems are avoided. Experimental results demonstrate the effectiveness of the proposed method to mild expression, illumination and occlusion. Referring to large expression variations and aging, our method exhibits some weakness. This suggests us to use a more complex OM set together with feature selection methods to model face variations. Also as future work, Gabor phase features can be further exploited for the fusion with Ordinal Measures, considering the good results obtaining by others using the phase information [6, 18].

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