# HISTOGRAM OF LOG-GABOR MAGNITUDE PATTERNS FOR FACE RECOGNITION

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## ABSTRACT

The Gabor-based features have achieved excellent performances for face recognition on traditional face databases. However, on the recent LFW (Labeled Faces in the Wild) face database, Gabor-based features attract little attention due to their high computing complexity and feature dimension and poor performance. In this paper, we propose a Gabor-based feature termed Histogram of Gabor Magnitude Patterns (HGMP) which is very simple but effective. HGMP adopts the Bag-of-Words (BoW) image representation framework. It views the Gabor filters as codewords and the Gabor magnitudes of each point as the responses of the point to these codewords. Then the point is coded by the orientation normalization and scale non-maximum suppression of its magnitudes, which are efficient to compute. Moreover, the number of codewords is so small that the feature dimension of HGMP is very low. In addition, we analyze the advantages of log-Gabor filters to Gabor filters to serve as the codewords, and propose to replace Gabor filters with log-Gabor filters in HGMP, which produces the Histogram of Log-Gabor Magnitude Patterns (HLGMP) feature. The experimental results on LFW show that HLGMP outperforms HGMP and it achieves the state-of-the-art performance, although its computing complexity and feature dimension are very low.

***Index Terms*—** face recognition, Gabor-based feature, Gabor filter, log-Gabor filter

## 1. INTRODUCTION

In the past decade, the Gabor-based features have been widely used for face recognition [1, 2, 3, 4, 5, 6]. These features take advantage of the multi-scale multi-orientation Gabor filters to achieve excellent performances. However, on the recent LFW face database [7] which is relatively large-scale, Gabor-based features attract little attention. This is partly due to the high computing complexity and feature dimension of these features which limit their applications to large-scale databases, and partly due to the poor performance of Gabor feature on LFW presented in the comparative study [8]. In this paper, we propose a Gabor-based feature termed Histogram of Gabor Magnitude Patterns (HGMP), which performs well with low computing complexity and feature dimension.

The proposed HGMP feature is motivated by the Bag-of-Words (BoW) image representation framework [9]. In BoW, there is a codebook whose codewords are meaningful primitives for coding the image information, and the interest points are coded according to these codewords. In HGMP, the Gabor filters are viewed as the codewords, and the Gabor magnitudes of each point are the responses of the point to the codewords. The magnitudes are processed by orientation normalization and scale non-maximum suppression to get the code for the point termed Gabor Magnitude Pattern (GMP). Then the point GMPs on non-overlapping image blocks are pooled to block GMPs which are concatenated and normalized to form the final HGMP feature for the image.

The codewords of Gabor filter make sense in the frequency domain. In the 2-D frequency plane, each Gabor filter covers a local region, and the filters cover the global plane together. However, the frequency responses of Gabor filters are overlapping on the low frequencies, which makes the Gabor responses correlated, while they contain little high frequencies, which makes the Gabor responses less discriminative. Moreover, the scale and orientation of Gabor filters are inseparable so that their localizations cannot be adjusted flexibly. The log-Gabor filters proposed by Field [10] overcome these problems. They have already been used in facial expression classification [11] and fingerprint image enhancement [12]. We propose to replace the Gabor filters with the log-Gabor filters in HGMP, which produces the Histogram of Log-Gabor Magnitude Patterns (HLGMP) feature. The experimental results show that HLGMP outperforms HGMP consistently across different parameter configurations.

The prior Gabor-based features mainly adopted Gabor filters as a preprocessing tool to get multiple Gabor filtered images, and then extracted the features based on these images [1,

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3, 5, 6]. This processing resulted in high computing complexity and feature dimension for these features. There are also Gabor-based features [2, 4] adopting the BoW framework as the proposed HGMP and HLGMP features. Specifically, Lei *et al*. [2] adopted the Gabor responses of each point as the point feature and learned codebook on this feature, and Xie *et al*. [4] adopted the Gabor magnitudes of the same filter in a patch centered at the point as the point feature and learned codebook on this feature for each filter. The two methods both involve codebook learning which needs a lot of training samples and can be time-consuming, and their codebook sizes are so large that their feature dimensions are very high. However, HGMP and HLGMP neither adopt the filters as the preprocessing tool nor adopt their responses as the feature to learn codebook. Instead, they directly adopts the filters as the codewords, which avoids the complex codebook learning and coding process. The filtering is just the coding, and the extra orientation normalization and scale non-maximum suppression are very efficient to compute. Therefore, the computing complexity of HGMP and HLGMP is very low. Moreover, the number of codewords, *i.e*. filters, is so small that the feature dimension of HGMP and HLGMP is very low. However, the performances of HGMP and HLGMP are excellent, and HLGMP outperforms the state-of-the-art features on LFW.

The main contributions of this paper is threefold: The first is the idea of taking Gabor filters as codewords, the second is an efficient coding method based on these codewords, and the third is the introduction of log-Gabor filters for face recognition with analyzing and demonstrating their advantages to the Gabor filters.

The rest of the paper is organized as follows. Section 2 describes the HGMP feature. Section 3 explains the log-Gabor filters. The experiments are presented in Section 4, and the conclusion is given in Section 5.

## 2. HISTOGRAM OF GABOR MAGNITUDE PATTERNS

The 2-D Gabor filter used for feature extraction in face recognition is defined as

$$G_{u,v}(\boldsymbol{z}) = \frac{\|\boldsymbol{k}_{u,v}\|^2}{\sigma^2} e^{-\frac{\|\boldsymbol{k}_{u,v}\|^2\|\boldsymbol{z}\|^2}{2\sigma^2}} \left(e^{i\boldsymbol{k}_{u,v}^{\mathrm{T}}\boldsymbol{z}} - e^{-\frac{\sigma^2}{2}}\right), \quad (1)$$

where $\|\cdot\|$ denotes the vector $\ell_2$ norm, and $\boldsymbol{k}_{u,v}$ is the center frequency of the filter, which is defined as

$$\boldsymbol{k}_{u,v} = [k_v \cos\phi_u, k_v \sin\phi_u]^{\mathrm{T}}, \quad (2)$$

where $k_v$ and $\phi_u$ are the scale and orientation of the filter. For the filters of $V$ scales and $U$ orientations, the scales and orientations are defined as

$$\begin{aligned} k_v &= k_0/f^v,\ v = 0, 1, \cdots, V-1, && (3)\\ \phi_u &= \pi u/U,\ u = 0, 1, \cdots, U-1, && (4) \end{aligned}$$

where $k_0$ is the maximal scale, and $f$ is the scale factor.

The frequency response of the Gabor filter is

$$F_{u,v}(\boldsymbol{w}) = e^{-\frac{\sigma^2\|\boldsymbol{w}-\boldsymbol{k}_{u,v}\|^2}{2\|\boldsymbol{k}_{u,v}\|^2}} - e^{-\frac{\sigma^2}{2}} e^{-\frac{\sigma^2\|\boldsymbol{w}\|^2}{2\|\boldsymbol{k}_{u,v}\|^2}}, \quad (5)$$

where the second term is produced by the $\exp(-\sigma^2/2)$ term in Eq. (1). It is subtracted to eliminates the DC component, and thus suppress the influence of illumination variation.

With the Gabor filters as the codewords, the Gabor magnitudes of each point measure the similarities of this point to the corresponding codewords. Therefore, the magnitudes contain the coding information, and the key is to convert the magnitudes to a robust and discriminative code.

We first arrange the Gabor magnitudes of $V$ scales and $U$ orientations at point $\boldsymbol{z}$ to a $U \times V$ magnitude matrix

$$\boldsymbol{M}(\boldsymbol{z}) = \begin{bmatrix} m_{11} & \cdots & m_{1V} \\ \vdots & \ddots & \vdots \\ m_{U1} & \cdots & m_{UV} \end{bmatrix}, \quad (6)$$

where $m_{ij}$ is the Gabor magnitude of $i^{th}$ orientation and $j^{th}$ scale. Then the magnitude matrix is coded in two steps:

- **Orientation normalization**. The magnitudes of all the orientations under the same scale are $\ell_2$ normalized:

  $$m_{ij} = \frac{m_{ij}}{\|\boldsymbol{m}_{\cdot j}\|}, \quad (7)$$

  where $\boldsymbol{m}_{\cdot j}$ is the $j^{th}$ column of $\boldsymbol{M}$.

- **Scale non-maximum suppression**. The magnitudes of all the scales under the same orientation are non-maximum suppressed:

  $$m_{ij} = \begin{cases} m_{ij}, & \text{if } m_{ij} = \max(\boldsymbol{m}_{i\cdot}), \\ 0, & \text{otherwise}, \end{cases} \quad (8)$$

  where $\boldsymbol{m}_{i\cdot}$ is the $i^{th}$ row of $\boldsymbol{M}$, and $\max(\cdot)$ returns the maximal element of the vector.

After the above steps, we get the GMP of the point

$$\boldsymbol{p}(\boldsymbol{z}) = [m_{11}, m_{21}, \ldots, m_{UV}]. \quad (9)$$

The GMP reflects the frequency character of the point, which is informative and discriminative. Moreover, orientation normalization makes GMP robust to illumination variations, and scale non-maximum suppression implements scale-selection and induces sparsity, which makes GMP more discriminative.

To represent the image, it is divided into non-overlapping $N \times K$ blocks of the same size: $\{R_{11}, R_{21}, \ldots, R_{NK}\}$, where $N$ and $K$ are the vertical and horizontal block numbers respectively. For each block $R_{ij}$, a GMP is obtained by summing all the point GMPs in the block:

$$\boldsymbol{p}(R_{ij}) = \sum_{\boldsymbol{z} \in R_{ij}} \boldsymbol{p}(\boldsymbol{z}). \quad (10)$$

Then the $N \times K$ block GMPs are concatenated and $\ell_1$ normalized to form the HGMP feature of the image

$$\boldsymbol{p}(I) = [\boldsymbol{p}(R_{11}), \boldsymbol{p}(R_{21}), \ldots, \boldsymbol{p}(R_{NK})], \tag{11}$$

$$\boldsymbol{h}(I) = \boldsymbol{p}(I)/|\boldsymbol{p}(I)|, \tag{12}$$

where $|\cdot|$ denotes the vector $\ell_1$ norm. Dividing the image into blocks provides spatial information for HGMP, and summing the point GMPs in the block provides invariance to small translation and rotation for HGMP. The extraction process of HGMP is summarized in Algorithm 1. As shown in the algorithm, the extraction of HGMP is very simple, and its dimension is $U \times V \times N \times K$, which is generally very low.

**Algorithm 1.** Histogram of Gabor Magnitude Patterns

**Input**: The image $I$, the scale and orientation numbers of filters $V$ and $U$, and the horizontal and vertical block numbers $K$ and $N$.

**Output**: The HGMP feature of the image $\boldsymbol{h}(I)$.

1. Design the $V$-scale $U$-orientation Gabor filters, and filter the image to get the Gabor magnitude matrix $\boldsymbol{M}(\boldsymbol{z})$ for each point.
2. Convert the Gabor magnitude matrix of each point to its GMP $\boldsymbol{p}(\boldsymbol{z})$.
3. Divide the images into non-overlapping $N \times K$ blocks of the same size, and average the point GMPs in each block to form the block GMP $\boldsymbol{p}(R_{ij})$.
4. Concatenate all the block GMPs and normalize it to produce the HGMP feature of the image $\boldsymbol{h}(I)$.

## 3. FROM GABOR FILTERS TO LOG-GABOR FILTERS

The log-Gabor filter has no explicit expression in the spatial domain, and it is defined in the frequency domain as

$$F_{u,v}(k, \phi) = e^{-\frac{[\log(k)-\log(k_v)]^2}{2[\log(\sigma_k)]^2}} e^{-\frac{(\phi-\phi_u)^2}{2\sigma_\phi^2}}, \tag{13}$$

where $k$ and $\phi$ are the radius and angle of the polar coordinate in the frequency plane corresponding to the scale and orientation in the Gabor filter, and $k_v$ and $\phi_u$ are the same scale and orientation of the center frequency as the Gabor filter. The log-Gabor filter has no DC component by itself without any extra term. The frequency responses of the Gabor and log-Gabor filters are shown in Fig. 1. Based on Eq. (5) and (13) and Fig. 1, we can find two important advantages of log-Gabor filters to Gabor filters.

First, the log-Gabor filter replaces the scale in the Gabor filter with its logarithmic form. As shown in Fig. 1 (a) and (b), this compresses the low frequencies and expands the high frequencies. As a result, the log-Gabor filters are less overlapping than Gabor filters on the low frequencies so that their responses are more independent, because low frequencies contain most energy of the images. Moreover, the log-Gabor filters retain more high frequencies than Gabor filters so that their responses are more discriminative, because high frequencies contain discriminative detailed texture information.

Second, for the Gabor filters, the $\sigma$ parameter adjusts both the localizations of scale and orientation. As a result, for a certain scale number, the orientation number of Gabor filters is limited, because the filters will be overlapping too much if there are too many orientations. However, for the log-Gabor filters, there are two parameters $\sigma_k$ and $\sigma_\phi$ adjusting the localizations of scale and orientation separately. As a result, the scale and orientation numbers of log-Gabor filters are more flexible to adjust. As shown in Fig. 1 (c) and (d), for 4 scales and 10 orientations, the Gabor filters are very overlapping, while the log-Gabor filters are better separated.

With these advantages, the log-Gabor filters are better than the Gabor filters to serve as the codewords in the frequency domain. Therefore, we replace the Gabor filters with log-Gabor filters in HGMP and get the HLGMP feature.

## 4. EXPERIMENTS

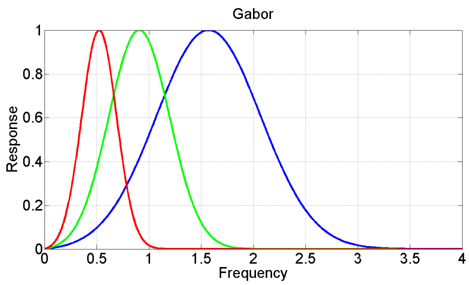
To validate the performance of the proposed HGMP and HLGMP features, they are applied for face verification on LFW View 2 dataset which contains 10 folds. We test on each fold with the other 9 folds learning the similarity threshold, and get 10 verification rates. The mean and standard deviation of the rates are reported. The similarity measure uses the Bhattacharyya coefficient

$$b(\boldsymbol{h}_1, \boldsymbol{h}_2) = \sum_i \sqrt{h_{1i} h_{2i}}\,, \tag{14}$$

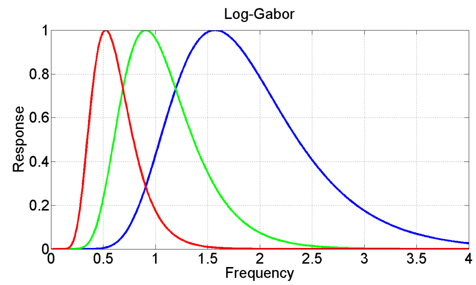
where $\boldsymbol{h}_1$ and $\boldsymbol{h}_2$ are the features of two face images, and $h_{1i}$ and $h_{2i}$ are the $i^{th}$ elements of them respectively.

We used the aligned version of face images in the LFW-a set [13] and cropped the centric $120 \times 80$ region as the face. The block number is set to $15 \times 10$. As to the scale and orientation numbers, in additional to the conventional 5-scale 8-orientation configuration, we also tested the 5-scale 10-orientation and 5-scale 12-orientation configurations to compare the performance of HGMP and HLGMP. For these configurations, the parameters of filters are set as: $k_0 = \pi/2$, $f = \sqrt{2}$, $\sigma = \pi$, $\sigma_k = 0.5$, and $\sigma_\phi = \pi/U$. Note that the $\sigma_\phi$ parameter is set adaptively with the orientation number to keep the log-Gabor filters well separated.

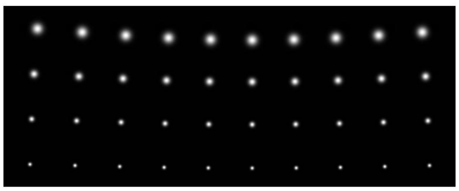
Table 1 shows the performance of HGMP and HLGMP with different scale-orientation configurations. The results reveal that HLGMP outperforms HGMP consistently, and its performance gain increases with the orientation number increasing. Note that adjusting the orientation number



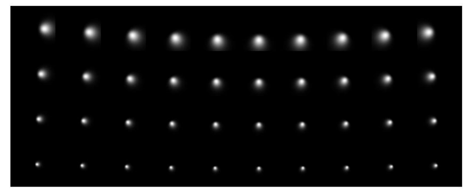

(a) 1-D Gabor frequency responses




(b) 1-D log-Gabor frequency responses



(c) 2-D Gabor frequency responses



(d) 2-D log-Gabor frequency responses

**Fig. 1**. The frequency responses of the Gabor and log-Gabor filters.

**Table 1**. The verification performance of HGMP and HLGMP with different scale-orientation numbers.

| Feature | Scale-Orein. | Mean | Std. |
|---|---|---|---|
| HGMP | S5-O8 | 0.7413 | 0.0063 |
| | S5-O10 | 0.7458 | 0.0058 |
| | S5-O12 | 0.7438 | 0.0051 |
| HLGMP | S5-O8 | 0.7507 | 0.0045 |
| | S5-O10 | 0.7593 | 0.0043 |
| | S5-O12 | 0.7605 | 0.0046 |

**Table 2**. The verification performances of different features.

| Features | Mean | Std. |
|---|---|---|
| GJD-BC-100 [8] | 0.6762 | 0.0069 |
| LARK [14] | 0.7223 | 0.0049 |
| LHS [15] | 0.7340 | 0.0040 |
| BiCov [16] | 0.7403 | 0.0032 |
| POEM-HS [17] | 0.7369 | 0.0059 |
| POEM-HS Flip [17] | 0.7522 | 0.0073 |
| I-LQP [18] | 0.7530 | 0.0080 |
| G-LQP [18] | 0.7530 | 0.0026 |
| HLGMP(S5-O10) | 0.7593 | 0.0043 |
| HLGMP(S5-O12) | **0.7605** | 0.0046 |

changes the performances of HGMP little, and even the performance degrades when the orientation number becomes too large. However, HLGMP can take advantage of the increased filters. Its performance continues improving with the orientation number increasing, although there is a saturation trend. The results validate the above analysis, and prove that the log-Gabor filters are better than the Gabor filters to serve as the codewords.

Table 2 shows the comparison results of the proposed HLGMP feature with the state-of-the-art features on LFW. Benefiting from the orientation normalization and scale non-maximum suppression, HLGMP outperforms all other features, although it is very simple and lightweight relative to them. Noting that HLGMP does not need any training, it can be an off-the-shelf feature which is very easy-to-use.

## 5. CONCLUSION

This paper proposes a novel Histogram of Gabor Magnitude Patterns (HGMP) feature for face recognition, which is motivated by the powerful Bag-of-Words (BoW) framework. HGMP takes the Gabor filters as codewords and designs an efficient coding method. In addition, the log-Gabor filters are introduced to replace log-Gabor filters in HGMP, which produces the Histogram of Log-Gabor Magnitude Patterns (HGMP) feature. Finally, HLGMP outperforms HGMP and achieves the state-of-the-art performance on LFW with very low computing complexity and feature dimension.

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