Statistical Modeling of Gabor Filtered Magnitude for Batik Image Retrieval

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***Abstract*—This paper presents an effective and efficient way on statistical modeling of Gabor filtered magnitude to generate an image feature descriptor. Two statistical distributions, i.e. Gaussian and Rayleigh distributions, are considered in the image feature extraction. The image feature is simply constructed by concatenating the distribution estimators of Gabor filtered magnitudes under different scales and orientations. As documented in the experimental section, the proposed method yields good performance in the Batik image retrieval system. In addition, the performance of Gabor feature can be improved by injecting the color feature in order to capture the color richness of an image.**

***Index Terms*—Batik; Gabor Filtered; Image Retrieval; Magnitude Component.**

I. INTRODUCTION

An image retrieval system searches a set of similar images in which these retrieved images have visual similarity with a given query image. These similarity criterions can be color similarity, textural similarity, edge similarity, etc. In image retrieval system, some image feature descriptors can be utilized to measure the similarity between the query image and a set of target images in the database. The image features obtained from Gabor filtered output have been successfully applied into image retrieval task [1], face recognition [2-3], etc. Another image features have also been reported to yield a good result in the image retrieval application such as Local Binary Pattern (LBP) feature [4-7] and its variants, Halftoning-Based Block Truncation Coding feature [8-9], etc. All of them are regarded as low-level feature in an image retrieval research.

In the Gabor-based feature descriptor, an image feature is often generated based on their statistical properties of the Gabor filtered output. The naive approach is to model the Gabor filtered output under Gaussian and Rayleigh distribution assumptions [1]. These methodologies assume the Gabor filtered output follows the Gaussian and Rayleigh behaviours. As reported in [1], the Gaussian and Rayleigh feature descriptor delivers a promising result on textural image retrieval system, especially in grayscale image format.

This paper extends the usability of the Gabor filtered output modeling for the Batik image retrieval system. Herein, all image features are derived from statistical estimators computed from Gabor filtered output. The main contributions of our proposed method can be highlighted as follow:

- Investigating the effectiveness of Gabor filtered magnitude for Batik image retrieval task.
- Performing the statistical modeling of Gabor filtered magnitude using Gaussian and Rayleigh distribution assumptions. In this paper, the Gabor wavelet is given as identical in [2-3]. Thus, we can further observe the correctness of statistical fitting of Gabor filtered magnitude when we apply different Gabor wavelet. Since the Gaussian and Rayleigh assumptions have been successfully applied in Gabor wavelet [1].
- Improving image retrieval performance by adding another feature. In this paper, we simply inject the color feature on Gabor-based image retrieval system.

II. MODELING OF GABOR FILTERED MAGNITUDE

A brief introduction of Gabor filtered magnitude is firstly introduced in this section. The statistical modeling of its magnitude is subsequently presented. In feature extraction stage, the Gabor filter extracts the textural information for all images in database and a given query image under specific distribution assumption. In this paper, the Gaussian and Rayleigh distributions can be chosen to generate image feature descriptor for the Batik image retrieval system.

A. Gabor Filtered Magnitude

Given a grayscale image $I(\vec{z})$ of size $X \times Y$, the Gabor wavelet generates a set of filtered images as follow:

$$G_{u,v}(\vec{z}) = I(\vec{z}) * \psi_{u,v}(\vec{z}) \tag{1}$$

where $\psi_{u,v}(\vec{z})$ and $\vec{z}$ denote the Gabor wavelet and pixel image positions, respectively. The symbol $*$ indicates the convolution operator. Whereas, the subscript u and v represents the orientation and scale of Gabor wavelet. Gabor wavelet generates a set of filtered images for all scales and orientations. The magnitude of each filtered image $G_{u,v}(\vec{z})$ can be easily computed as:

$$\mathcal{M}_{u,v}(\vec{z}) = \sqrt{\mathrm{Re}^2\{G_{u,v}(\vec{z})\} + \mathrm{Im}^2\{G_{u,v}(\vec{z})\}} \tag{2}$$

where $\mathcal{M}_{u,v}$ denotes the Gabor filtered magnitude. The symbols $\mathrm{Re}\{\cdot\}$ and $\mathrm{Im}\{\cdot\}$ indicate the operator to obtain the real and imaginary part of a given input. At the end of convolution operation, Gabor filter produces a set of Gabor filtered magnitudes with U orientations and V scales. The proposed scheme employs the Gabor filter under identical paramater as previously used in [2-3].

B. Modeling with Gaussian Distribution Assumption

The Gabor filtered magnitude has a strong tendency to follow Gaussian nature. It has bell-shape with heavy-tailed. Thus, the Gaussian distribution can be chosen as an underlying assumption to model the Gabor filtered magnitude. The Probability Density Function (PDF) of Gaussian distribution is formally defined as:

$$p(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} \quad (3)$$

where μ and σ represent the mean value and standard deviation, respectively. Let $X = \{x_1, \dots, x_N\}$ be independent and identically distributed samples drawn from Gabor filtered magnitude at (u,v). Thus, the log-likelihood of X can be computed under Gaussian assumption as:

$$\mathcal{L}(\mu,\sigma|X) = -\frac{1}{2}N\log 2\pi - N\log\sigma - \frac{\sum_{i=1}^{N}(x_i-\mu)^2}{2\sigma^2} \quad (4)$$

Using simple mathematics manipulation, the closed-form estimators of Gaussian distribution from X can be derived as follows:

$$\hat{\mu} = \frac{\sum_{i=1}^{N} x_i}{N} \quad (5)$$

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{N}(x_i-\hat{\mu})^2}{N}} \quad (6)$$

In the image retrieval system, the image feature descriptor can be composed from these two estimators as:

$$f_{\mu\sigma} = \{\hat{\mu}_{0,0}, \hat{\sigma}_{0,0}, \hat{\mu}_{0,1}, \hat{\sigma}_{0,1}, \dots, \hat{\mu}_{U-1,V-}, \hat{\sigma}_{U-1,V-1}\} \quad (7)$$

The feature dimensionality of this descriptor is $2UV$. Where the U and V denote the number of orientations and scales of Gabor filter, respectively.

C. Modeling with Rayleigh Distribution Assumption

The Rayleigh distribution may offer an alternative way to model the Gabor filtered magnitude. The Rayleigh PDF is formally defined as:

$$p(x|\gamma) = \frac{x}{\gamma^2} exp\left(-\frac{x^2}{2\gamma^2}\right) \quad (8)$$

where $\gamma > 0$ forms the distribution shape. The log-likehood of X under Rayleigh distribution assumption is:

$$\mathcal{L}(\gamma|X) = N\{\log 1 - 2\gamma\} + \sum_{i=1}^{N}\log x_i - \frac{1}{2\gamma^2}\sum_{i=1}^{N} x_i^2 \quad (9)$$

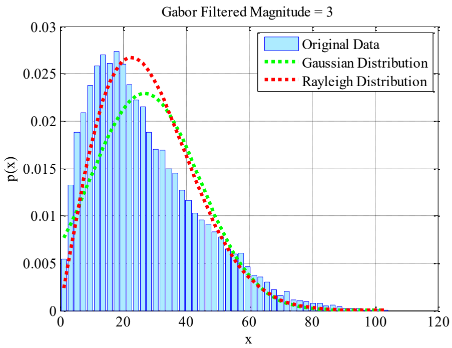
The closed-form estimator for the Rayleigh distribution using X can trivially computed as follow:

$$\hat{\gamma} = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2} \quad (10)$$

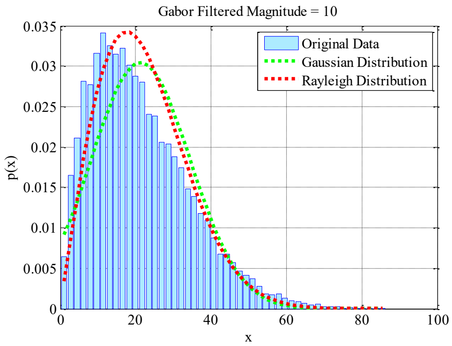
Thus, the image feature descriptor derived from Rayleigh distribution assumption is given as:

$$f_\gamma = \{\hat{\gamma}_{0,0}, \hat{\gamma}_{0,1}, \dots, \hat{\gamma}_{U-1,V-1}\} \quad (11)$$

Thus, the feature dimensionality of this image descriptor is simply UV. The dimensionality of f_γ is only a half of $f_{\mu\sigma}$. Figure 1 shows statistical modeling of Gabor filtered magnitude using Gaussian and Rayleigh distributions. Gabor filtered magnitude is well fitted with Gaussian and Rayleigh distributions as depicted in this figure.



(a)



(b)

Figure 1: Statistical fitting of Gabor filtered magnitude under (a) Gaussian and (b) Rayleigh assumptions, respectively.

III. Experimental Results

Some extensive experiments have been conducted to examine and investigate the performance of Gabor-based image retrieval system. Herein, the batik image database is chosen to validate the effectiveness and usability of the proposed method. This image database consists of various images with different colors, textural patterns, shape, etc. It contains 1552 color images which are further divided into 97 image classes, such that each image class consists of 16 color images. Some image classes are labeled with Javanese sematic names such as Batik Parang Barong, Batik Parang Gendreh, Batik Kawung, Batik Truntum, etc. All images in the same class are regarded as the same even though they have different visual appearances. It causes the challenging task for content-based image retrieval system. Figure 2 shows example of some Batik images used in the experiment.

To measure the similarity degree between the query image and a set of target images in the database, the proposed method employs the distance metrics such as Manhattan (L_1), Eucliean (L_2), and modified Canberra distances [8-9]. The performance of the proposed image retrieval system is objectively measured in terms of Precision and Recall [4-9]. Higher value of these values indicates better result on image retrieval system. In this experiment, the number of orientations and scales of Gabor wavelet are chosen as $U = 8$ and $V = 5$, respectively. It indicates the dimensionalities of $f_{\mu\sigma}$ and f_γ are 80 and 40, respectively.

Figure 2: Example of Batik image database.

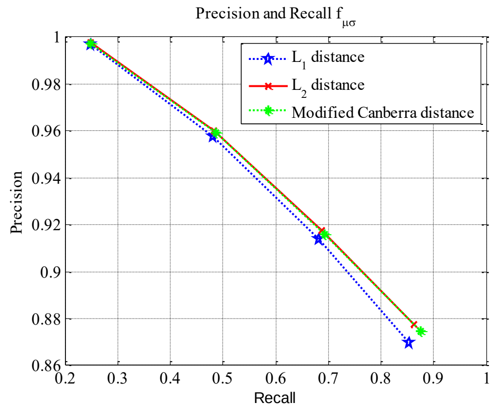
A. *Practical Application*

This subsection evaluates the correctness of the proposed method by visual investigation. In this experiment, an image is randomly drawn from image database and turned as query image. In order to search a set of similar images in database, the nearest neighbor searching under L_2 distance metric. Figure 3 gives example of image retrieval system by turning $f_{\mu\sigma}$ and f_{γ} as image features. A query image is at the top-left corner for each figure, whereas a set of retrieved images are subsequently given and ordered in ascending order based on their L_2 scores against the query image. As shown in this figure, the Gabor feature gives a promising result on the Batik image retrieval system. The $f_{\mu\sigma}$ yields better result compared to f_{γ} as reported in this figure. A set of retrieved images contain similar appearance with the query image. Yet, the Gabor feature has proven its usability in practical application of image retrieval system.

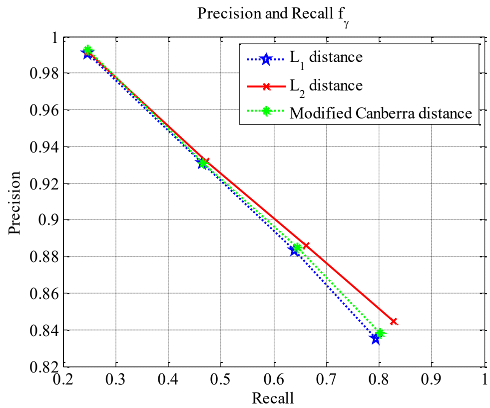
Figure 3: Example of image retrieval systems using (a-b) $f_{\mu\sigma}$, and (c-d) f_{γ} over different query images.

B. *Effect of Different Distance Metrics*

The proposed method is then evaluated objectively to further investigate its performance under different distance metrics. All images in database are turned as query image, the precision and recall values are subsequently calculated for all query images. Herein, the number of retrieved images are set as $L = \{4,8,\ldots,16\}$. Figure 4 gives the performance comparison for image features $f_{\mu\sigma}$ and f_{γ} under various distance metrics. For image feature $f_{\mu\sigma}$, the L_2 and modified Canberra distances yield almost identical performance indicating with their similar precision and recall values. However, the L_2 distance gives the best performance on f_{γ}. This experiment tells that the choice of distance metric affects on the overall performance in Batik image retrieval system.



(a)



(b)

Figure 4: Effect of different distance metrics on (a) $f_{\mu\sigma}$ and (b) f_{γ}.

C. *Comparison of Gaussian and Rayleigh Features*

It will be more interesting to compare the performance of $f_{\mu\sigma}$ and f_{γ} under similar distance metric on Batik image retrieval system. In this comparison, the image retrieval performances are measured in terms of Precision and Recall values with $L = \{4, 8, \ldots,16\}$ under L_2 and modified Canberra distances. Since these two distances yield the best performance in both image features. Again, all images in database are considered as query image. Figure 5 reports the performance comparison between $f_{\mu\sigma}$ and f_{γ}. The feature $f_{\mu\sigma}$ offers better image retrieval performance compared to that of f_{γ} under L_2 and modified Canberra distance. It makes sense since the feature dimensionality $f_{\mu\sigma}$ is higher than f_{γ}, i.e. half feature dimensionality. However, the image retrieval performances are not much different between $f_{\mu\sigma}$ and f_{γ}. Thus, the f_{γ} becomes more preferable for image retrieval applications in the limited storage constraint.

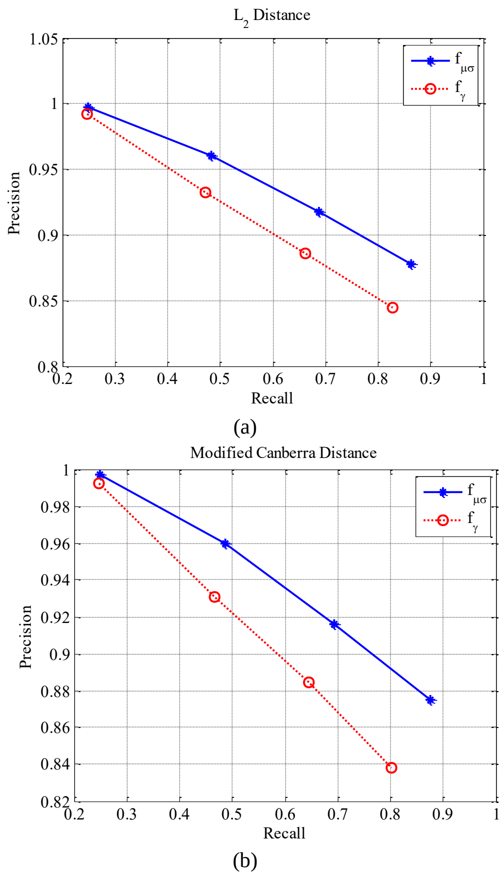


Figure 5: Precision and recall comparison between $f_{\mu\sigma}$ and f_{γ} under (a) L_2 and (b) Modified Canberra distance metrics, respectively.

D. Injecting the Color Feature

In this experiment, the effectiveness of Gabor feature descriptor is evaluated by adding an additional image feature. Herein, the Color Histogram Feature (CHF) [8-9] is involved for the Batik image retrieval system. The Gabor feature extracts the textural information of an image, whereas the CHF captures the color information. The similarity degree between the query image q and target image t in database using fusion of Gabor feature and CHF is given as follow:

$$d(q,t) = \alpha_1 \delta(f^q, f^t) + \alpha_2 \delta(c_{min}^q, c_{min}^t) + \alpha_3 \delta(c_{max}^q, f_{max}^t), \quad (12)$$

where f, c_{min}, and c_{max} denote the Gabor feature, CHF min quantizer, and CHF max quantizer, respectively. The symbol $\delta(\cdot,\cdot)$ represents the distance metric such as L_1, L_2, or modified Canberra distance. The $\{\alpha_1, \alpha_2, \alpha_3\}$ is the similarity weighting constants which can be $\{0,1\}$. Table 1 reports the experimental results of the proposed method by injecting the color feature on the Batik image retrieval system. Herein, the results are given in percentage (%). As shown in this table, the proposed method yields better image retrieval performance by adding an additional image feature, i.e. CHF. Since the color information of an image is considered in similarity matching, especially in the similarity distance computation.

E. Comparison Against Former Schemes

An additional experiment was also carried out to further investigate the proposed method effectiveness. The performance of the proposed method is compared against several former schemes on Batik image retrieval system. In this experiment, the comparison is measured in terms of retrieval rate in percentage (%). Table 2 summarizes the performance comparison between the proposed method and former schemes on the Batik image retrieval system. As reported in this table, the proposed method yields better retrieval accuracy compared to the former schemes under the Batik image database. It is worth noted that the proposed method requires a slight lower feature dimensionality compared to the former schemes. This experiment clearly reveals that the Gabor feature can be used in the Batik image retrieval.

Table 1
Effect of Injecting the Color Feature

Image Feature	Dimensionality	Similarity Distance		
		L1	L2	Modified Canberra
$f_{\mu\sigma}$	80	86.95	87.77	87.48
$f_{\mu\sigma} + f_{min}$	112	93.27	87.78	96.72
$f_{\mu\sigma} + f_{max}$	112	82.78	66.47	88.95
$f_{\mu\sigma} + f_{min} + f_{max}$	144	93.71	89.02	96.55
f_{γ}	40	83.53	84.47	83.83
$f_{\gamma} + f_{min}$	72	92.99	87.85	95.13
$f_{\gamma} + f_{max}$	72	80.77	68.19	80.68
$f_{\gamma} + f_{min} + f_{max}$	104	93.54	89.05	95.47

Table 2
Performance Comparison between Proposed Method and Former Schemes

Method	Feature Dimensionality	Accuracy (%)
LBP [4]	59	92.57
LTP [5]	118	95.65
CLBP [6]	118	95.17
LDP [7]	236	93.52
$f_{\mu\sigma} + f_{min} + f_{max}$	144	96.55
$f_{\gamma} + f_{min} + f_{max}$	104	95.47

IV. Conclusions

A statistical modeling of Gabor filtered magnitude for effective Batik image retrieval has been presented in this paper. Two statistic distributions are investigated to generate image feature descriptors. As reported in experimental section, the proposed method offers a promising result on Batik image retrieval application.

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