Batik Image Retrieval Using ODBTC Feature and Particle Swarm Optimization

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***Abstract*—This paper proposes an effective and efficient approach to Batik image retrieval using Ordered Dither Block Truncation Coding (ODBTC) feature. Similarity degree between two images can be easily investigated under similarity distance score between their feature descriptors. As documented in the experimental section, the feature descriptor outperforms the former existing schemes under Batik image database. The Particle Swarm Optimization (PSO) iteratively searches the optimal similarity weighting constants to further improve the image retrieval performance. Thus, a set of retrieved images become more satisfactory and acceptable for user desire and preference.**

***Index Terms*—Batik; Image Retrieval; Particle Swarm Optimization; Similarity Weighting Constants.**

I. INTRODUCTION

Batik is Indonesian traditional clothing pattern which has very high artistic value and unique repeatable pattern. In some cultural society such as Javanese culture, batik plays an important role in the daily life. Batik always appears on most of the traditional Javanese ceremonies such as traditional wedding ceremony, coronation ceremony of Javanese King, Javanese New Year eve, etc. In the image and video processing field, the batik can be viewed as textural image with some special properties. Thus, the batik image can be regarded and processed as texture image in digital processing.

The content-based image retrieval system offers a convenient way in the process of browsing, retrieving, and searching a set of desired images which are stored in the image database. The image database is a set of images stored and organized in storage device. The size of image database is often huge in which a process on searching specific image manually will require a high time causing unpleasant condition for user.

This paper offers a simple approach for solving the problem occurred in the batik image retrieval. The proposed method generates an effective image feature descriptor from ODBTC data stream. This image feature descriptor is very convenient for the content-based image retrieval system. This paper extends the usability of ODBTC image feature in the content-based batik image retrieval system. This image feature is to improve the image retrieval performance and to solve the aforementioned problem in the former existing batik image retrieval systems.

II. BATIK IMAGE RETRIEVAL SYSTEM

This section presents the batik image retrieval system. Figure 1 illustrates the schematic diagram of the image retrieval system. Firstly, the computation of image features descriptor is detailed presented. These image feature descriptors are derived from the ODBTC color quantizers and bitmap image. There are two features obtained from ODBTC processing. The first feature, namely Color Histogram Feature (CHF), can be regarded as color feature, whereas the other feature, namely Bit Pattern Histogram Feature (BHF), can be viewed as texture feature. The similarity distance is subsequently calculated from these two image feature descriptors to measure the similarity between two images on the searching process of an image. Please refer [1-3] for detail explanation of ODBTC color image compression and its feature extraction to obtain CHF and BHF.

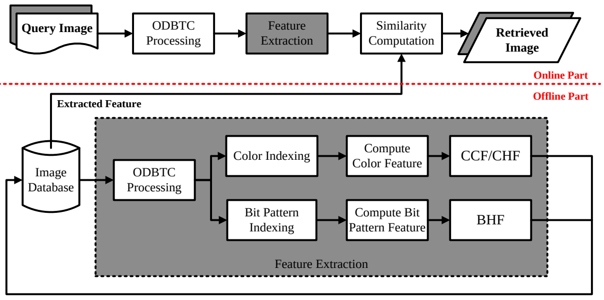

Figure 1: Schematic diagram of image retrieval system.

In our proposed image retrieval system, the similarity degree between two images can be easily measured based on the distance score between their image feature descriptors. The similarity degree between the query image and target image using the ODBTC feature can be simply computed using L_1, L_2, χ^2, or Modified Canberra distance. Since the CHF and BHF are from different modalities, a naive approach to combine these two features is to use the weighting strategy. These similarity distances with weighting strategy can be formally defined as follow:

- L_1 distance:

$$\delta(query,target)=\alpha_1\sum_{k=1}^{N_{min}}\left|CHF_{min}^{query}(k)-CHF_{min}^{target}(k)\right|+\alpha_2\sum_{k=1}^{N_{max}}\left|CHF_{max}^{query}(k)-CHF_{max}^{target}(k)\right|+\alpha_3\sum_{k=1}^{N_b}\left|BHF^{query}(k)-BHF^{target}(k)\right| \quad (1)$$

- L_2 distance:

$$\delta(query,target)=\left[\alpha_1\sum_{k=1}^{N_{min}}\left(CHF_{min}^{query}(k)-CHF_{min}^{target}(k)\right)^2+\alpha_2\sum_{k=1}^{N_{max}}\left(CHF_{max}^{query}(k)-CHF_{max}^{target}(k)\right)^2+\alpha_3\sum_{k=1}^{N_b}\left(BHF^{query}(k)-BHF^{target}(k)\right)^2\right]^{\frac{1}{2}} \quad (2)$$

- χ^2 distance:

$$\delta(query, target) = \alpha_1 \sum_{k=1}^{N_{min}} \left(\frac{CHF_{min}^{query}(k) - CHF_{min}^{target}(k)}{CHF_{min}^{query}(k) + CHF_{min}^{target}(k) + \varepsilon} \right)^2 + \alpha_2 \sum_{k=1}^{N_{max}} \left(\frac{CHF_{max}^{query}(k) - CHF_{max}^{target}(k)}{CHF_{max}^{query}(k) + CHF_{max}^{target}(k) + \varepsilon} \right)^2 + \alpha_3 \sum_{k=1}^{N_b} \left(\frac{BHF^{query}(k) - BHF^{target}(k)}{BHF^{query}(k) + BHF^{target}(k) + \varepsilon} \right)^2 \quad (3)$$

- Modified Canberra distance:

$$\delta(query, target) = \alpha_1 \sum_{k=1}^{N_{min}} \frac{\left| CHF_{min}^{query}(k) - CHF_{min}^{target}(k) \right|}{CHF_{min}^{query}(k) + CHF_{min}^{target}(k) + \varepsilon} + \alpha_2 \sum_{k=1}^{N_{max}} \frac{\left| CHF_{max}^{query}(k) - CHF_{max}^{target}(k) \right|}{CHF_{max}^{query}(k) + CHF_{max}^{target}(k) + \varepsilon} + \alpha_3 \sum_{k=1}^{N_b} \frac{\left| BHF^{query}(k) - BHF^{target}(k) \right|}{BHF^{query}(k) + BHF^{target}(k) + \varepsilon} \quad (4)$$

where CHF_{min}^{query} and CHF_{max}^{query} denote CHF features of query image, CHF_{min}^{target} and CHF_{max}^{target} represent the CHF features of target image. While the BHF^{query} and BHF^{target} indicate the BHF feature of query image and target image, respectively. The symbol ε denotes a small number to avoid mathematical division error. The values $\{\alpha_1, \alpha_2, \alpha_3\}$ denote the similarity weighting constants representing the percentage contribution of CCF_1 and BHF features on the image retrieval system. Higher value on the similarity weighting constants indicates higher contribution of specific image feature on the system. The zero value for these constants mean that a specific image feature is not involved in the image retrieval system.

III. SIMILARITY WEIGHTING CONSTANTS OPTIMIZATION

The similarity distance computation plays an important role in the image retrieval system. Different choice on distance metrics yields different image retrieval performance. However, finding the best similarity distance metric is hard task since it data-dependent. An easy way to determine the similarity distance metric is to use the weighting scenario. Given a specific distance metric, the weighting constants are adjusted to yield the best image retrieval performance. However, this task is very time consuming while it is conducted manually.

To further reduce the time computation on finding the best weighting constants, the Particle Swarm Optimization (PSO) is selected on determining the optimum value of weighting process. Herein, the similarity weighting constants are iteratively adjusted using PSO algorithm to obtain the optimum image retrieval performance. The similarity weighting constants are coded as swarm particle which are iteratively updated based on their fitness function. The PSO algorithm is data-dependent on selecting the optimum similarity weighting constants. The PSO particle with the highest fitness function represents the optimum image retrieval performance.

The PSO firstly randomizes the velocity moves inside a specific searching space [8-9]. On each iteration, the particle velocity and particle location are updated using the following formula:

$$v_i(t+1) = wv_i(t) + c_1\xi_1[p_i - x_i(t)] + c_2\xi_2[p_g - x_i(t)] \quad (5)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (6)$$

The x_i and v_i denote the particle location and velocity, respectively. The variable w is the inertia weight, and c_1 and c_2 are positive constants. The ξ_1 and ξ_2 are uniformly random number in range [0, 1].

Let T be a set of training images for PSO iteration. The PSO obtains the optimum similarity weighting constants as maximization problem as follow:

$$\max_{\{\alpha_1^*, \alpha_2^*, \alpha_3^*\}} Accuracy\{T | \alpha_1, \alpha_2, \alpha_3\} \quad (7)$$

where $Accuracy\{T | \alpha_1, \alpha_2, \alpha_3\}$ is the image retrieval performance over all training images. Figure 2 gives illustration the PSO process on finding the optimum similarity weighting constants.

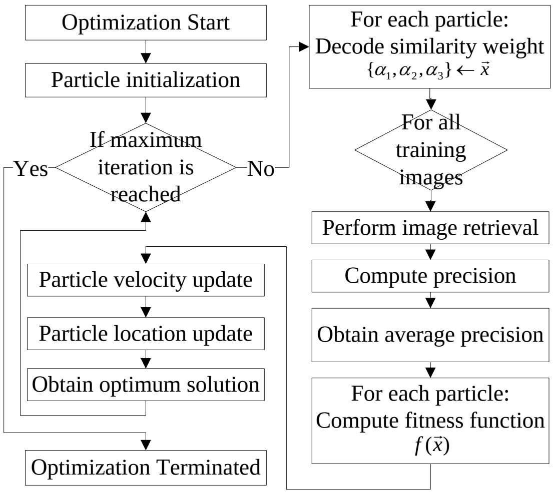

Figure 2: Schematic diagram of swarm optimizer on image retrieval system.

IV. EXPERIMENTAL RESULTS

This section reports the usability and effectiveness of the proposed image feature descriptor on content-based image retrieval system. The successfulness of the image retrieval system is further examined by manually investigation or using performance evaluation metrics. The manual investigation simply considers the similar appearance between the query image and target image using human visual observation. While the other performance evaluation involves these two metrics, namely Average Precision Rate (APR) and Average Recall Rate (ARR) [1-7].

A. Practical Application on Batik Image Retrieval

This subsection presents the usability and effectiveness of the proposed image retrieval system under Batik image database. This image database contains 97 image classes containing various Batik patterns, rich color compositions, invariant complexity, scale, shape, etc. Some of these image classes can be labeled as Batik Mega Mendung, Batik Sido Luhur, Batik Sido Drajat, Batik Parang Rusak, etc. Each image class consists of 16 images, thus the total image in Batik image database is 1552. All Batik images in the same class are regarded as the similar images (relevant image). Figure 3 shows some image samples from Batik image database.

Figure 3: Some samples from Batik image database.

The practical usability of the proposed image retrieval system is examined using the visual investigation of Batik image database. Figure 4 demonstrates the application of proposed image retrieval system on Batik image database using $CHF + BHF$ features with feature dimensionality. This result clearly reveals that the proposed method is very suitable for Batik image retrieval as shown with a high number of correct retrieved images under human visual investigation.

Figure 4: A set of retrieved images from Batik database using $CHF + BHF$ features. An image in the first column is a query image, and a set of retrieved images are subsequently shown in the same row ordered in ascending manner based on their similarity distance score.

B. Effect of Similarity Distance Metric on Batik Image Retrieval

This subsection delivers the effect of similarity distance metric on Batik Image Retrieval System. The similarity distance metric plays an important role in the image retrieval system. Better choice on similarity distance metric yields better performance on the image retrieval. Different similarity distance metric gives different similarity score causing different outcome on a set of retrieved images.

In this experiment, the performance evaluations are conducted using APR and ARR metrics to make a fair investigation. The performance of image retrieval system is evaluated over different distance metrics (i.e. L_1, L_2, χ^2, and Modified Canberra distance) with 48 feature dimensionality of $CHF + BHF$). The number of retrieved images is $L = \{4, 8, \ldots, 16\}$. Figure 5 shows the effect of different distance metrics over various image block sizes using $CHF + BHF$ feature. The Modified Canberra distance yields the best performance compared to the other distance metrics. Thus, the Modified Canberra distance is a good candidate for measuring similarity degree on Batik image retrieval.

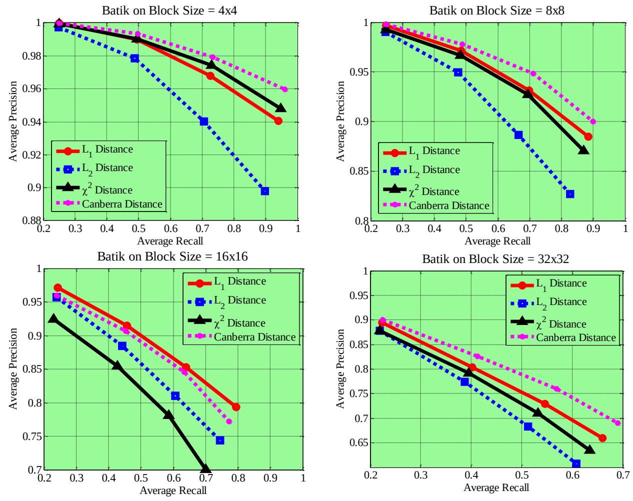

Figure 5: Effect of different distance metrics over various image block sizes on Batik image retrieval using $CHF + BHF$ features.

C. Performance Comparison on Batik Image Retrieval

In this experiment, the proposed method performance is compared to the former textural image retrieval schemes such as Local Binary Pattern (LBP) [4], Local Ternary Pattern (LTP) [5], Completed Local Binary Pattern (CLBP) [6], and Local Derivative Pattern (LDP) [7]. To make a fair comparison, the Modified Canberra distance is utilized to measure similarity degree between query image and target images for all methods. The similarity weighting constants are set as $\{\alpha_1 = \alpha_2 = \alpha_3 = 1\}$. The number of retrieved image is set as $L = 16$. =As summarized in this Table 1, the proposed method with different feature dimensionality outperforms to the former existing schemes. It is noteworthy that the $CHF + BHF$ with feature dimensionality 48 (the lowest feature dimensionality) gives the best performance compared to the LBP method and its variants. It clearly reveals that the proposed method is very effective on Batik image retrieval system.

Table 1
Performance Comparisons against Former Schemes on Batik Image Retrieval

Method	Feature Dimensionality	Accuracy (%)
LBP [4]	59	92.57
LTP [5]	$118\{2 \times 59\}$	95.65
CLBP [6]	$118\{2 \times 59\}$	95.17
LDP [7]	$236\{4 \times 59\}$	93.52
Proposed Method	$48\{N_{min} = N_{max} = N_b = 16\}$	95.97
Proposed Method	$96\{N_{min} = N_{max} = N_b = 32\}$	97.27
Proposed Method	$192\{N_{min} = N_{max} = N_b = 64\}$	97.51
Proposed Method	$384\{N_{min} = N_{max} = N_b = 128\}$	97.68

D. Effect of Swarm Optimizer on Batik Image Retrieval

On the previous experiments, the similarity weighting constants are simply set as $\{\alpha_1 = \alpha_2 = \alpha_3 = 1\}$. It is regarded as un-optimized setting since it considers all image feature descriptors with the same percentage contribution. In this experiment, the similarity weighting constants are set as non-negative value. The determination of these values is regarded as optimization value which can be effectively searched using PSO algorithm. Herein, the PSO iteratively updates the similarity weighting constants to obtain the best image retrieval performance. The PSO employs 30 swarm particle on decoding the candidate of optimum similarity weighting constants. The maximum iteration of PSO is simply set at 100 to avoid premature convergence. The fitness function of PSO is computed based on the APR value (with $L = 16$) over a set of training images using the proposed image feature descriptor. The PSO is run for 30 times to investigate stability of PSO on finding the optimum solution. The proposed method exploits ODBTC with image block size 4×4 for generating image feature. The color and bit pattern codebook sizes are set as $N_{min} = N_{max} = N_c = N_b = 16$. The similarity degree is measured using the Modified Canberra distance. Different image feature descriptor requires different PSO run on deciding the optimum similarity weighting constants.

Figure 6 shows the PSO convergence history for the best and worst run on Batik image retrieval over various image feature descriptors. As shown from this figure, the PSO converges on one optimum solution at finding the suitable similarity weighting constants. As reported in Table II, the proposed method with optimized similarity weighting constants outperforms the un-optimized setting. The PSO is also very stable on finding the optimum solution as indicated with a low standard deviation over all PSO runs.

Addition experiment is conducted to further investigate the effect of swarm optimizer in terms of visual investigation. Figure 7 depicts the visual investigation of the proposed image retrieval system with un-optimized setting and optimized setting in the similarity weighting constants determination. As shown in this figure, the optimized version of similarity weighting constants gives better image retrieval result compared to un-optimized setting which can be judged based on visual investigation.

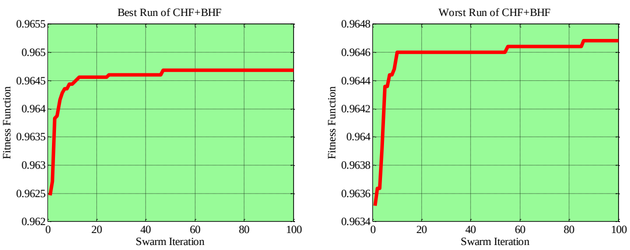

Figure 6: The PSO convergence history of the best (left) and worst run (right) on Batik image retrieval using $CHF + BHF$ features.

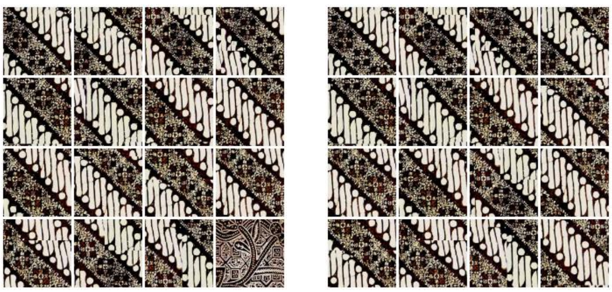

Figure 7: Visual investigation of retrieved image sets using un-optimized (left) and optimized similarity weighting constants (right) on Batik image retrieval with $CHF + BHF$ features.

Table 2
Performance of Optimized Similarity Weighting Constants on Batik Image Retrieval

Batik Image Retrieval	Accuracy
Un-optimized	95.97
Best	96.47
Worst	96.47
Mean	96.47
Median	96.47
Standard Deviation	0.00
Optimum similarity weighting constants, $\boldsymbol{\alpha}^*$	$\boldsymbol{\alpha}_1^* = 0.2814$ $\boldsymbol{\alpha}_2^* = 0.2136$ $\boldsymbol{\alpha}_3^* = 0.7393$

V. Conclusions

An effective and efficient way for the content-based batik image retrieval has been proposed and presented in this paper. In this system, two image features are employed i.e. Color Histogram Feature (CHF) and Bit Histogram Feature (BHF). As reported in experimental section, the proposed method gives promising result for image retrieval under batik image database. The swarm optimizer effectively increases the image retrieval accuracy by selecting a suitable similarity weighting constants in iterative manner. Herein, the searching process is regarded as optimization task.

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