International Journal of Technology (2016) 4: 654-662
ISSN 2086-9614

QUERY REGION DETERMINATION BASED ON REGION IMPORTANCE INDEX AND RELATIVE POSITION FOR REGION-BASED IMAGE RETRIEVAL

Pasnur[1*], Agus Zainal Arifin[2], Anny Yuniarti[2]

[1] *Sekolah Tinggi Manajemen Informatika dan Ilmu Komputer AKBA, Kampus STMIK AKBA Tamalanrea, Makassar 90245, Indonesia*
[2] *Department of Informatics Engineering, Faculty of Information Technology, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya 60111, Indonesia*

(Received: August 2015 / Revised: September 2015 / Accepted: April 2016)

ABSTRACT

An efficient Region-Based Image Retrieval (RBIR) system must consider query region determination techniques and target regions in the retrieval process. A query region is a region that must contain a Region of Interest (ROI) or saliency region. A query region determination can be specified manually or automatically. However, manual determination is considered less efficient and tedious for users. The selected query region must determine specific target regions in the image collection to reduce the retrieval time. This study proposes a strategy of query region determination based on the Region Importance Index (RII) value and relative position of the Saliency Region Overlapping Block (SROB) to produce a more efficient RBIR. The entire region is formed by using the mean shift segmentation method. The RII value is calculated based on a percentage of the region area and region distance to the center of the image. Whereas the target regions are determined by considering the relative position of SROB, the performance of the proposed method is tested on a CorelDB dataset. Experimental results show that the proposed method can reduce the Average of Retrieval Time to 0.054 seconds with a 5x5 block size configuration.

Keywords: Local binary pattern; Region-based image retrieval; Region importance index; Relative position; Region code; Saliency region

1. INTRODUCTION

Content-Based Image Retrieval (CBIR) is browsing, searching, and navigating images from a large image collection based on visual contents (Shrivastava & Tyagi, 2014). CBIR has advantages over traditional techniques that utilize text annotation. With the massive growth of multimedia data, there are too many images that have no annotation or improper annotation (Shete & Chavan, 2012; Singh & Ahmad, 2014). These conditions will decrease the accuracy of image retrieval and provide reasoning to use CBIR, which is independent of text annotation.

A popular query technique in CBIR is Query by Example (QBE). In this technique, the user provides an image as a query to be retrieved. The features of the image will be extracted and compared with the feature of all images in the collection. Any closest feature comparison will be displayed as a retrieval result (Vimina & Jacob, 2013).

Feature extraction may occur globally or locally. A global feature, like in Wang et al. (2011)

*Corresponding author's email: pasnur@akba.ac.id, Tel./Fax. +62-411-588371
Permalink/DOI: http://dx.doi.org/10.14716/ijtech.v7i4.1546

and Wang and Wang (2013), often cannot reflect the desire of users. The use of a local feature, like in Vimina and Jacob (2013), Zhu et al. (2013), Shrivastava and Tyagi (2014), Yang and Cai (2014), and Cheng et al. (2015), is recommended to overcome this problem. Local feature extraction can be performed by forming any regions on a query image; this it is known as Region-Based Image Retrieval (RBIR) (Shrivastava & Tyagi, 2014).

An efficient RBIR system must consider query region determination technique and target regions in the retrieval process. A query region is a region that must contain a Region of Interest (ROI) or saliency region. Query region determination can be specified manually (Shrivastava & Tyagi, 2014) or automatically (Yang & Cai, 2014). The selected query region must determine specific target regions in the image collection to reduce retrieval time (Shrivastava & Tyagi, 2014).

Shrivastava and Tyagi (2014) proposed an RBIR system by utilizing a region code for a region that targets selection. A query image is divided into blocks with 3×3, 5×5, and 7×7 block size configuration. The user must select the ROI or saliency region manually on the query image. Manual saliency region selection is considered less efficient and tedious for users. Automatic saliency region is recommended to overcome this problem.

The selected saliency region will overlap with one or more region blocks in image query; this it is known as the Saliency Region Overlapping Block (SROB). During similarity calculation, SROB can be compared with blocks in the target images in two ways: fixed location matching (Tian et al., 2000) or all-blocks matching (Lee & Nang, 2011). Fixed location matching has some disadvantages due to spatial dependency. Relevant images on different blocks are difficult to retrieve using fixed location matching. All-blocks matching can be employed to solve this problem. The SROB moves over the whole image, block by block, and compares all blocks of the target image with the query region. However, this method will increase retrieval time with an increased number of blocks.

Retrieval time can be reduced by comparing a few, but not all, blocks that are related to the initial position of the SROB. Retrieval time works on the assumption that the probability of finding the query region is higher in the parts of the database image where the SROB is and its related adjacent locations (Shrivastava & Tyagi, 2014). All SROBs are compared with their associated blocks separately and their relative positions are ignored. This method can be developed further by considering the relative position of all SROB to produce a more efficient RBIR.

This study proposes a strategy of query region determination based on RII value and relative position of SROB to produce a more efficient RBIR. The entire region is formed by using a mean shift segmentation method. The RII value is calculated based on a percentage of the region area and region distance to the center of the image. Whereas the target regions are determined by considering the relative position of SROB, the similarity between the query and the image collection is measured by a histogram of their local binary pattern (LBP) feature.

2. METHODOLOGY

The proposed system framework was adopted from the old system framework (Shrivastava & Tyagi, 2014) by adding two blocks as a novel method in this study. Figure 1 depicts the proposed method, which consists of three main blocks: process in image collection, process in query image, and process of similarity measure between query image and all images in the collection.

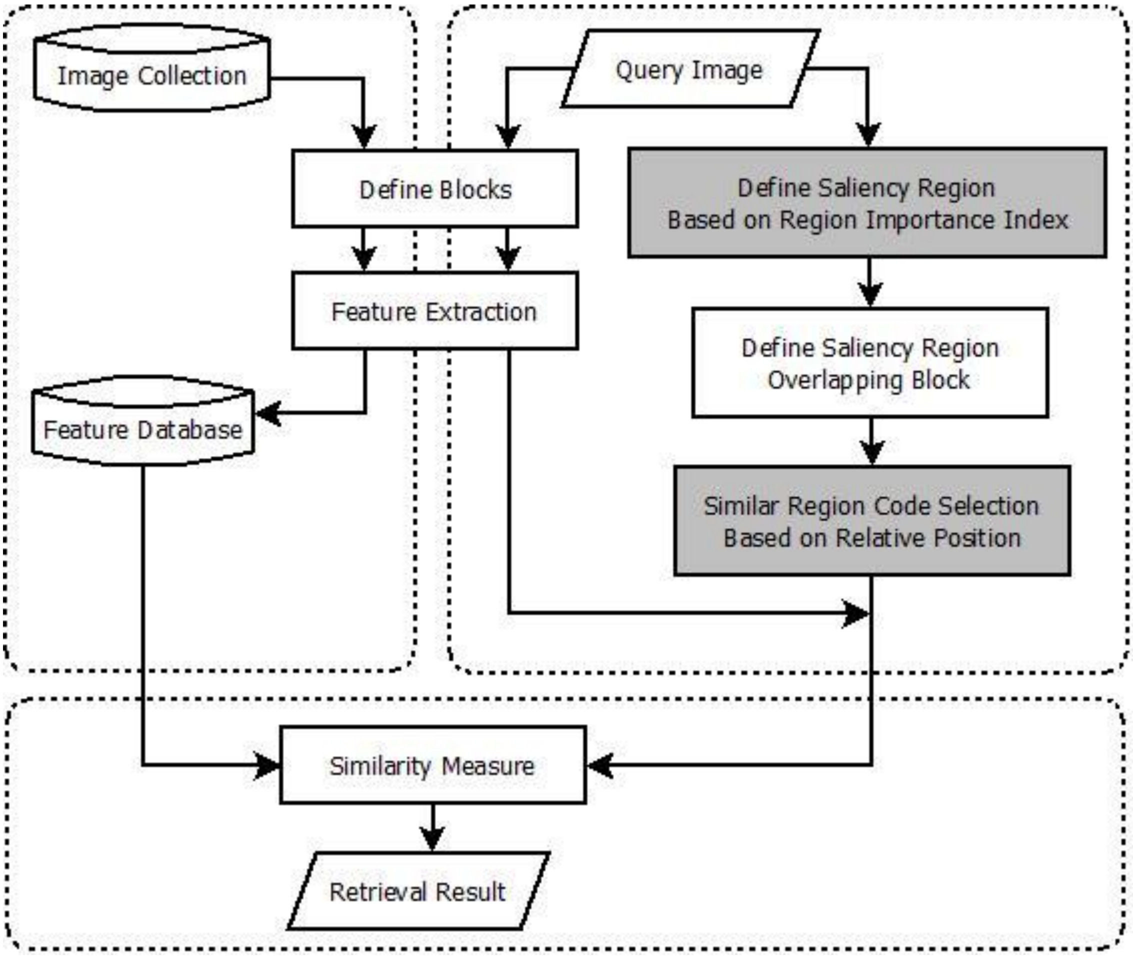

Figure 1 Proposed system framework

All images in the collection will be divided into blocks with 3×3 or 5×5 block size. Each block of the image is assigned a 4-bit code depending on its spatial location relative to the central region, as shown in Figure 2. Starting from the first lower-order bit, each of the four bits in the region code specifies left, right, bottom, and top region of the image, respectively. For example, the code of the region that lies on top left of the central region will have a region code 1001. As the middle region of the image generally contains most important details of the image, it has been assigned a unique code (1111) as an exception because its direction cannot be decided and it must be included in all comparisons (Shrivastava & Tyagi, 2014).

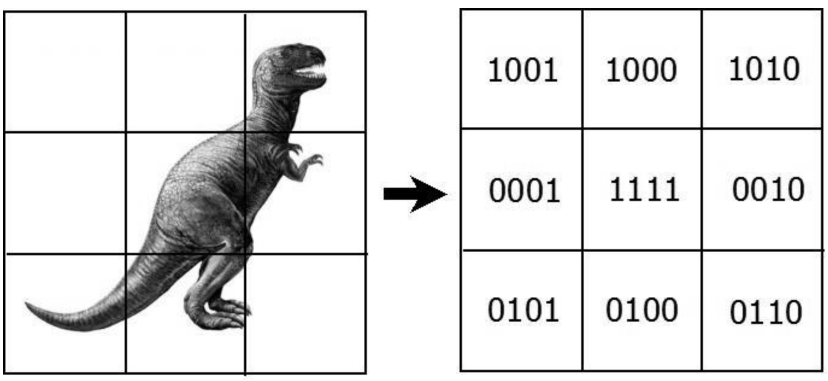

Figure 2 Example of image with region code

The LBP feature will be extracted from all blocks as their visual property. The LBP value describes a pixel of the image based on its neighbor pixels' gray level (Zhu et al., 2013). Given a pixel, the LBP value can be calculated by comparing it with its neighbors as

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c).2^P, \qquad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

where g_c is the gray value of the center pixel, g_p represents the value of neighboring pixels, P is the total number of neighbors, and R is the radius of the neighborhood. After generation of the LBP code for each pixel in the image, a histogram of LBP value is used to represent the texture image. All LBP values and their histograms were stored in a feature database and will be used in a similarity measure (Shrivastava & Tyagi, 2014).

Instead manual saliency region selection which used in (Shrivastava & Tyagi, 2014), we employ automatic saliency region selection based on Region Importance Index (RII) value. RII works on the assumption that saliency region usually located in the center of image and has the largest area (Yang & Cai, 2014). Based on the assumption, RII value of region r_i in image A is defined as

$$RII(r_i) = \frac{(r_i)_{area}}{A_{area}} \left(1 - \frac{2 * \sqrt{(r_{ix} - x)^2 + (r_{iy} - y)^2}}{\sqrt{L(A)^2 + H(A)^2}} \right) \tag{2}$$

where $(r_i)_{area}/A_{area}$ is the region r_i area percentage, (r_{ix},r_{iy}) is the coordinate of region r_i, (x,y) is the center coordinate of image A, and $L(A)$ and $H(A)$ are the length and height of image A, respectively. The query image is segmented first by using mean shift clustering (Tao et al., 2007) to obtain all regions in the image. The RII value of all regions will be calculated and the region with the highest value is the saliency region.

The selected saliency region will overlap with one or more block regions in the query image; this is called the SROB. The system will evaluate all SROB based on their Dominant Color Descriptor (DCD). The SROB with the largest overlap is selected as the reference. All other SROB having same DCD as the reference are selected for further steps (Shrivastava & Tyagi, 2014).

The last step before performing the retrieval process is to find a similar region code for all selected SROB. The similarity between region codes is determined by looking for the region codes having 1 in the same bit positions as the SROB region code. This similarity is determined by performing a logical AND operation between region codes. If the outcome of the AND operation is not 0000, then the two region codes are similar. Our system work based on the assumption that the probability of finding the query region is higher in the parts of the database image where the SROB is located and in its related adjacent locations or regions with a similar region code. While Shrivastava and Tyagi (2014) found similar region codes individually for all selected SROB, we consider their relative position to accomplish the same thing.

In an example shown in Figure 3a, there are three SROB, SROB-1 (region code 1001), SROB-2 (region code 0001), and SROB-3 (region code 1111), that represent the selected saliency region. By using the method in Shrivastava and Tyagi (2014), we can find a similar region code for each SROB individually and ignore their relative position. They are SROB-1={1001, 1000, 1010, 0001, 1111, 0101}, SROB-2={1001, 0001, 1111, 0101}, and SROB-3={1001, 1000, 1010, 0001, 1111, 0010, 0101, 0100, 0110}, respectively. In this case, SROB-1 must scan six regions, SROB-2 must scan four regions, and SROB-3 must scan nine regions. The system must scan each image in the collection 19 times.

The proposed method considers the relative position of all SROB to further reduce the number of similar region codes. The SROB having the fewest number of similar region codes is selected as the reference. As shown in Figure 3, SROB-2 is selected as the reference because it has the fewest numbers of similar region codes. All similar region codes are evaluated by placing the reference SROB on similar region codes one by one and, at the same time, placing other SROB by keeping their relative position to reference SROB, as shown in Figures 3b–3e. Figure 3b shows an invalid condition because SROB-1 is out of the image. Based on Figures 3c–3e, which shows three valid conditions, we can find a valid similar region code for each SROB: they are SROB-1={1001, 1000, 0001}, SROB-2={0001, 1111, 0101}, and SROB-3={1111, 0010, 0100}. In this case, based on the proposed method, SROB-1, SROB-2, and SROB-3 must each scan three regions. The system must scan each image in the collection nine times; this it is more efficient than the Shrivastava and Tyagi (2014) method.

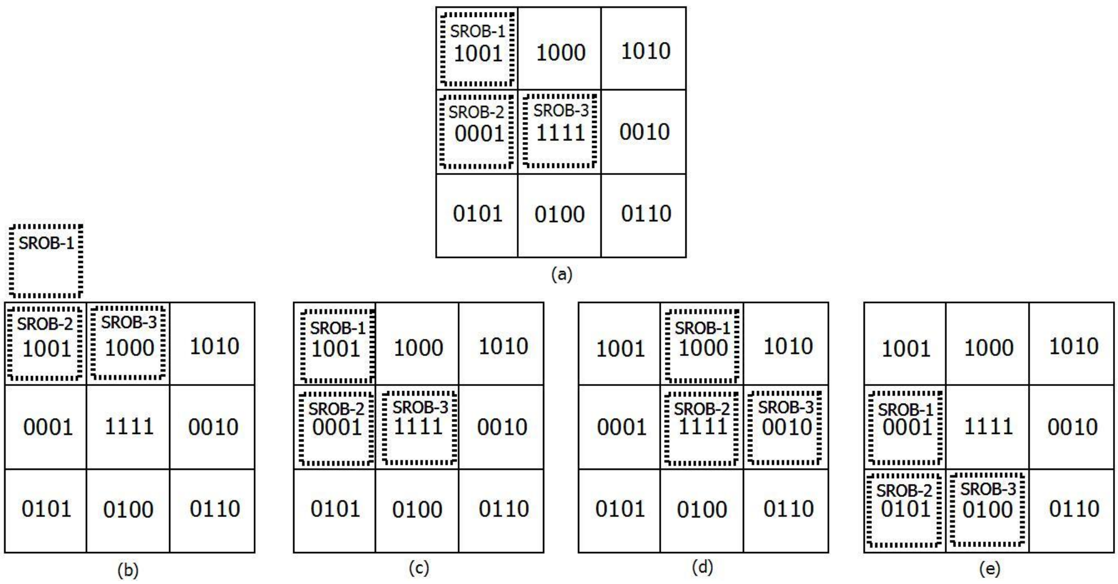

Figure 3 Similar region code selection based on relative position

A similarity measure is performed by comparing the histogram of the LBP with the SROB and its valid similar region code for each image in the collection as

$$D\left(B_r, I^j\right) = \min\left(LD_i\left(B_r, I^j_{b_i}\right)\right), i = 1 \dots n \tag{3}$$

where $D(B_r, I^j)$ represents the distance between SROB B_r and the jth image of the collection, and $LD_i\left(B_r, I^j_{b_i}\right)$ represents distance between SROB B_r and each block in the image I having a similar region code with SROB B_r. The system will scan image target n time as the total number of similar region codes. The similarity measure uses Euclidean distance and finds the nearest distance as a result.

The proposed method is tested on a CorelDB dataset that consists of 10 categories. Each category contains 20 images containing the same object. Five query images will be selected from each category and used in the retrieval process, so the total query in this study is 50. Some of query images are shown in Figure 4. The performance of the proposed method will be evaluated by using precision, recall, Averaged Normalized Modified Retrieval Rank (ANMRR), and Average of Retrieval Time.

Figure 4 Some of Query Images

3. RESULTS

The Average of Retrieval Time describes how long a similarity measure is performed for one image in the collection for a query. The Average of Retrieval Time was calculated based on the results of the 50 queries that were tested. Table 1 shows the experimental result for the average retrieval time of both the Shrivastava method and the proposed method with 3×3 and 5×5 block size configuration. As shown in Table 1, the proposed method is faster than the Shrivastava method, which it means that proposed method is more efficient than the Shrivastava method.

Table 1 Experimental result for the average retrieval time

Method	Average Retrieval Time (Seconds)	
	3×3	5×5
Shrivastava Method	0.091	0.295
Proposed Method	**0.032**	**0.054**

The effectiveness of the system is measured by using precision, recall, and ANMRR. Precision represents the percentage of the relevant image in the retrieval result to the number of images in the retrieval result. Recall represents the percentage of the relevant image in the retrieval result to a number of relevant in the collection. ANMRR represents the quality of a CBIR system based on the number of relevant images and their rank (position) in the retrieval result. ANMRR does not only determine if a correct answer is found from the retrieval results, but it also calculates the rank of the particular answer in the retrieval results. A lower ANMRR value represents better performance. Figures 5, 6, and 7 show the experimental results for precision, recall, and ANMRR, respectively.

4. DISCUSSION

The proposed method is faster than the Shrivastava method based on a comparison of their average retrieval time, as shown in Table 1. In the case of the 3×3 block size configuration, the proposed method can reduce retrieval time to 0.059 seconds or 65% of retrieval time in the Shrivastava method. In the case of the 5×5 block size configuration, the proposed method can reduce retrieval time to 0.241 seconds or 82% of retrieval time in the Shrivastava method. Time reduction reached by the proposed method is due to considering the relative position of SROB in determining similar region codes. Using this technique, the proposed method can eliminate some regions in the retrieval process that have little chance of visual similarity with the query. Finally, the proposed method can reduce retrieval time without losing its effectiveness.

Figures 5 and 6 show the average precision value and recall value, respectively, from 5 to 50 numbers of the retrieval result.

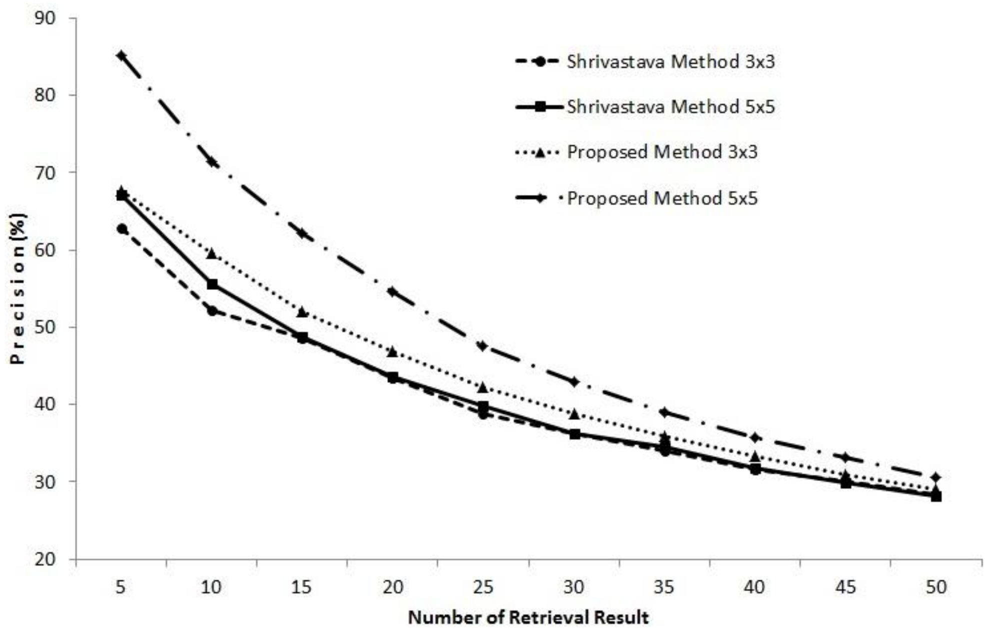

Figure 5 Experimental result for precision

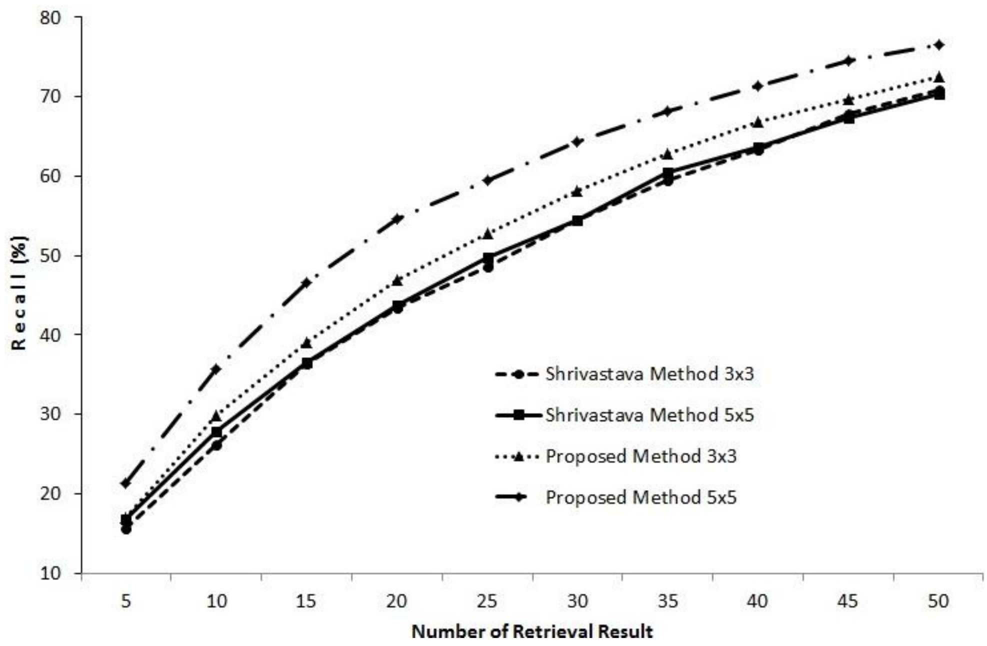

Figure 6 Experimental Result for Recall

In this range, the proposed method is better than the Shrivastava method in both 3×3 and 5×5 block size configurations. Increasing the number of retrieval results above 50 will decrease the precision value because the number of relevant images is only 20 in each category. Increasing the number of the retrieval result will increase the recall value as well because all relevant images will be retrieved. These results prove that the proposed method has better performance in effectiveness based on average precision value and average recall value. The proposed method only eliminates some regions in the retrieval process that have little chance of visual similarity with the query, thus average retrieval time will be reduced without losing precision or recall.

Figure 7 shows the ANMRR value for 20 to 50 numbers of the retrieval result. The ANMRR value of the proposed method is lower than the Shrivastava method in both 3×3 and 5×5 block size configurations. The lower ANMRR value indicates better performance. The proposed method has better performance based on ANMRR value because it can retrieve more relevant images in the top ranks than the Shrivastava method by eliminating some regions in the retrieval process that have little chance of visual similarity with the query.

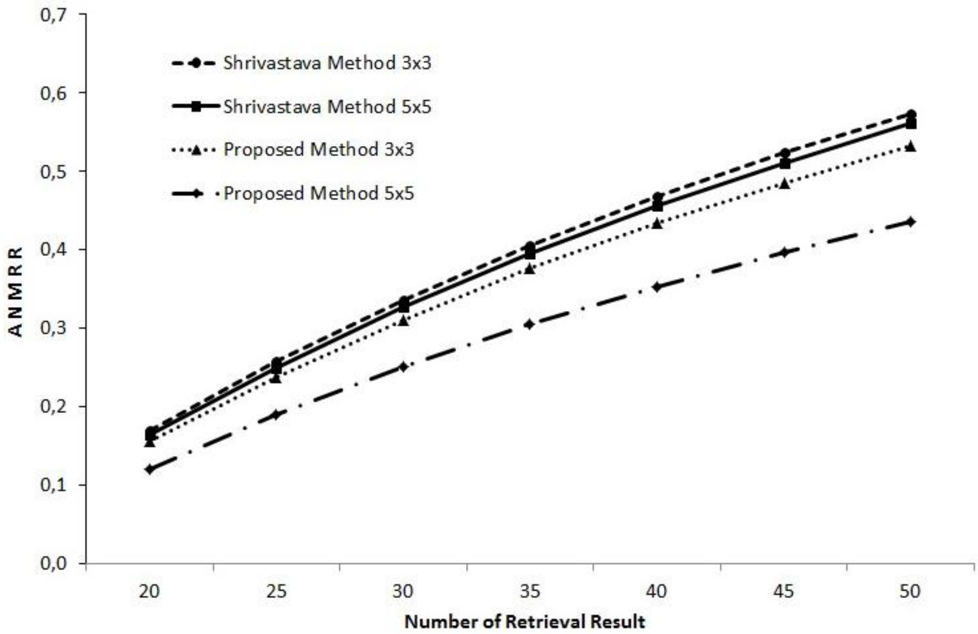

Figure 7 Experimental Result for ANMRR

All experimental results show that the 5×5 block size configuration is better than the 3×3 both in effectiveness and efficiency. Configuring the block in size 5×5 can extract the LBP feature in more detail and produce the number of the region better than the 3×3 block size, which increases the effectiveness of the system and reduces retrieval time.

Experimental results for precision, recall, and ANMRR of the Shrivastava method sometimes overlap between 3×3 and 5×5 block size configurations. It shows that increasing the block size configuration from 3×3 to 5×5 by using the Shrivastava method sometimes give not a significant result. The Shrivastava method ignores the relative position of SROB, which has a role in improving the performance of a RBIR system, in the retrieval process. This drawback is addressed in the proposed method to provide a better result.

5. CONCLUSION

This study has been conducted to determine the query region based on the RII and the relative position of SROB to produce a more efficient RBIR. Experimental results show that the proposed method can reduce the average retrieval time to 0.054 seconds with a 5×5 block size configuration or can reduce 82% of retrieval time in the Shrivastava method. The proposed method is more efficient than the Shrivastava method without losing its effectiveness value. The proposed method has a lower ANMRR value than the Shrivastava method, which indicates its better performance. The proposed method is better than the Shrivastava method in terms of both efficiency and effectiveness.

6. REFERENCES

Cheng, M.M., Zhang, G.X., Mitra, N.J., Huang, X., Hu, S.M., 2015. Global Contrast Based Salient Region Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume 37(3), pp. 1–8

Lee, J., Nang, J., 2011. Content Based Image Retrieval Method using the Relative Location of Multiple ROIs. *Advances in Electrical and Computer Engineering*, Volume 11(3), pp. 85–90

Shete, D.S., Chavan, M.S., 2012. Content Based Image Retrieval : Review. *International Journal of Emerging Technology and Advanced Engineering*, Volume 2(9), pp. 85–90

Shrivastava, N., Tyagi, V., 2014. Content Based Image Retrieval based on Relative Locations of Multiple Regions of Interest using Selective Regions Matching. *Information Sciences*, Volume 259, pp. 212–224

Singh, B., Ahmad, W., 2014. Content Based Image Retrieval: A Review Paper. *International Journal of Computer Science and Mobile Computing*, Volume 3(5), pp. 769–775

Tao, W., Jin, H., Zhang, Y., 2007. Color Image Segmentation based on Mean Shift and Normalized Cuts. *IEEE Transactions on Systems, MAN, and Cybernetics*, Volume 37(5), pp. 1382–1389

Tian, Q.T.Q., Wu, Y.W.Y., Huang, T.S., 2000. Combine User Defined Region of Interest and Spatial Layout for Image Retrieval. In: *Proceedings 2000 International Conference on Image Processing*, Voume 3, pp. 746–749

Vimina, E.R., Jacob, K.P., 2013. A Sub-block based Image Retrieval using Modified Integrated Region Matching. *International Journal of Computer Science Issues*, Volume 10(1), pp. 686–692

Wang, X., Wang, Z., 2013. A Novel Method for Image Retrieval based on Structure Elements' Descriptor. *Journal of Visual Communication and Image Representation*, Volume 24(1), pp. 63–74

Wang, X.Y., Yu, Y.J., Yang, H.Y., 2011. An Effective Image Retrieval Scheme using Color, Texture and Shape Features. *Computer Standards & Interfaces*, Volume 33(1), pp. 59–68

Yang, X., Cai, L., 2014. Adaptive Region Matching for Region-based Image Retrieval by Constructing Region Importance Index. *IET Computer Vision*, Volume 8(2), pp. 141–151

Zhu, C., Bichot, C.E., Chen, L., 2013. Image Region Description using Orthogonal Combination of Local Binary Patterns Enhanced with Color Information. *Pattern Recognition*, Voume 46(7), pp. 1949–1963