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AN AUTOMATED CONTENT-BASED IMAGE RETRIEVALSYSTEM FORMARINE LIFE IMAGES

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***Abstract:*-Content based image retrieval (CBIR) has been an active and fast growing research area in both image processing and data mining. Thedynamic nature of CBIRcomplements the drawbacks of Text Based Image Retrieval (TBIR).Malaysia has been recognized with a rich marine ecosystem. Challenges of these images are low resolution, translation, and transformation invariant. In this paper, we have designed anautomated CBIR system to characterize the species for future research.We compared various image descriptors and the combination of multiple features. Our results show that the combination of shape and colour features yields higher precision and recall value. We also proposed segmentation as pre-processing step for our CBIR system. For the automated segmentation, we use the saliency and the region growing methods. Our findings show that the region-growing method has better accuracy.**

***Keywords:*-Content-based image retrieval, Region Growing, FD, Zernike Moment, PHOG, Image segmentation**

I. INTRODUCTION

The importance of Content-Based Image Retrieval (CBIR) is motivated by the increasing desire for retrieving images from growing digital image databases over the Internet. In the past decade a lot of research and work has been done on CBIR systems such as the QBIC (Query by Image Content), Photobook and Visualseek [1]. The CBIR is fast, efficient and can automatically extract low-level features (such as shape, colour and texture) from images to assess the similarity between different images. The CBIR system has also been developed for art image retrieval [2], medical image [3] and plants image [4, 5]. The domain specific CBIR usually require its own specialized set of image descriptors.

The diversity of marine life in Malaysia requires the manpower of marine scientist to identify marine species when doing surveillance work in the field. They would like to recognize the species categories without manually looking for each category to match the species.To meet these requirements, content based image retrieval via query by example has been proposed. To the best of our knowledge CBIR system for marine species has not been developed. The closest relevant work is by Petrakis [6]which use manually segmented marine life silhouette images in shape matching application.

In our previous publication [7], several low-level features were evaluated and the shape features yieldbetter results than the colour and the texture features. In another publication [8],segmentation was evaluated to achieve in better accuracy.Segmentation was implemented as preprocessing step and it has improved the precision and recall results.

In this paper, we would like to extend our previous work to develop an automated CBIR system for marine life images. There are two objectives of this paper. The first one is to compare more image descriptors and looking for the possibility to combine these descriptors. The second objective is to evaluate two methods for automated segmentation and compare their performances with manual segmentation.

II. The PROPOSEDCBIR SYSTEM

Fig. 1 shows the proposed architecture of CBIR system using query by example. In the proposed CBIR system, we divide our system into two parts: segmentation and retrieval.

A. Features Evaluation and Combination

When retrieving images from database, user commonly express the search requirement using high level concept embedded in the query image. The high level concept is approximated by the low level visual features such as the color, texture and shape feature [7].Due to the complexity of the marine life images, it will be more effective to use the low level visual features in an integrated fashion. The color histogram [7] for example only gives the global color distribution in the image and no spatial relationship between the color patterns is represented. Whereas Colour Correlogram (CC), and Coloured Pattern AppearanceModel (CPAM) [11]concentrate on spatial information of an image. In view of the highly textured appearance of the marine species image, texture features will be useful.Texture description that has been used in CBIR system includes gray-level co-occurrence matrices, local binary patterns (LBP) and Markov random fields [9]. These features are available only for gray level images and do not exploit the rich colour attribute of the marine life.

Common shape descriptor such as moment and Fourier descriptors [10,11]requires the clean silhouette or contour of the object to be segmented.Our previous publication [7] proves shape to be better than colour and texture. Each features have their drawbacks and to reduce those drawbacks combination of these features is implemented.

In this section we will combine shape with colour to test retrieval performance. Feature extraction techniques like Pyramid of Orientation Histogram (PHOG) [10], Fourier Descriptor (FD), Zernike Moment (ZM) Colour Correlogram (CC), Coloured Pattern Appearance Model (CPAM) and Colour Histogram (HIST) will be combined. Features are combined by adding shape feature (ZM, FD) with colour feature colour feature (CC, CPAM, HIST). These features are combined in a series format [shape feature vector, colour feature vector].

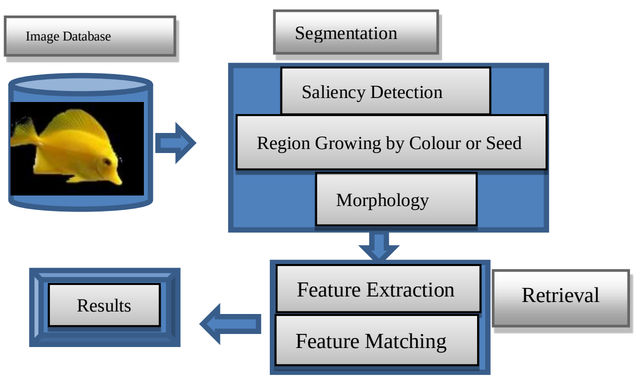


Fig. 1: - proposed architecture of CBIR system.

B. Preprocessing Segmentation

Our finding [7] clearly provesshape to be the prominent feature in retrieval of marine life images.The problem in the marine life images are the region of interest in an image is not clear which makes the feature extraction not reliable. The images are usually blurred making it difficult for system to differentiate between the object and the background. Toovercome these problems we recommend segmentation to the marine life images before they are added into the database.In our case we did automated/manual segmentation of the images concentrating on region of interest (ROI) and compared them with the whole images.

III.SEGMENTATION

i. Manual segmentation

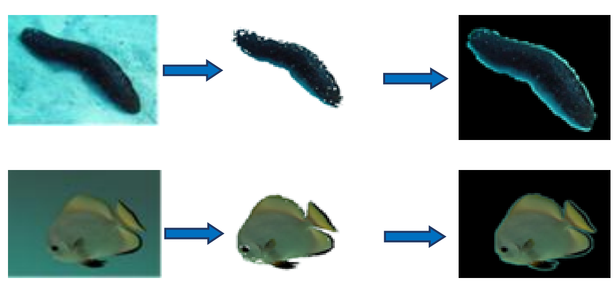
Initially in pre-processing the images are manually segmented to only have region of interest and rest black background so our techniques can only work on the region. From our study we discovered a lot of our feature techniques works better if they are provided with a contour or region to work on rather than the whole image specially the shape features. Once the images are segmented features are extracted using the feature extracting, followed by distance matrix on them.

ii. Automated segmentation

After knowing segmentation [8] helps a lot in the accuracy of our system, automated segmentation is applied Fig 1. To have automated system manual segmentation is replace with automated segmentation. Performing automated segmentation on marine images had a lot of issues, as there were a lot of information in the marine images and the quality of the images were issues. To overcome a lot of these issues each techniques went through a lot of processing to have maximum of region of interest and to have minimum of background. There are three ways in which the automated segmentation was performed which are discuss below.When segmentation is applied to images the one most prominent issue is the distortion or missing region in image while segmentation, to overcome this morphology is applied to the images. Morphology removes small distortion areas and add missing region in the image.

a. Saliency Detection

The proposed segmentation method starts by converting the RGB colour images to LAB colour space because LAB can better exaggerate the lighting in the image which helps in better segmentation.Fig. 2 illustrate the block diagram of saliency detection. Saliency value measure algorithm [8] is used which highlights the region with brighter light and are being focused in the image .Thresh-holding is applied to removes the unwanted less bright area/background. This gives a region of interest with a lot of distortion and some regions missing. One of the reason is the use of brighter region to extract the region. Morphology is applied to the image making the segmented image to be smooth and less distortion.



Original Image Saliency measure value morphology

Fig. 2: - segmentation block diagram for saliency detection

b. Region Growing using seed

The proposed segmentation method starts by assigning a seed pixel, which is a pixel from region of interest.The region is iteratively grown by comparing all unallocated neighbouring pixels to the region.The difference between a pixel's intensity value and the region's mean,is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. After each pixel added the new mean is calculated to have a better ROI.This process stops when the intensity difference between region mean andnew pixel become larger than a certain threshold (*t*).This process is carried out until the end of image and all the neighbouring pixel location is calculated and outputted. The output image is a black and white image of ROI which is then converted to RGB image. To remove the distortion in the image and fill in missing region morphology is allied.

c. Region Growing using colour

The proposed segmentation method starts by converting the RGB colour images to LAB colour space. All the pixel from the image will be subtracted then square will be taken followed by square root, reason for doing so is to find all the pixel with the similar pixel properties and not have any negative value.

Once we have an image with the difference from the pixel, a thresh hold with a value is applied which means any pixel with value less than thresh hold value is meant to be in the region of interest .We applied different thresh hold values and applied the optimal one. Morphology is applied to have a smooth region of interest. Feature extraction techniques are applied followed by distance matrix.

IV. Feature Evaluation

In order to evaluate the effectiveness of the CBIR system, we have selected shape and colour based feature that has been used successfully for image indexing and image recognition in the past.

PHOG has been used for object recognition and tested on the MPEG-7 and Caltech-101 dataset with good results [10]. The feature is obtained by computing the edge orientation histogram from multiple levels ofedge image spatial grids.In the proposed system, we use 3 levels (L=3) of spatial grids and all the orientation histogram of each levels and cells are concatenated. Each level is given similar weight. The 360 degree angle range is quantized into 8 bins.The PHOG feature represents both texture and local shape in its feature vector.

Zernike moment (ZM) and Fourier descriptor (FD) are two of the mostly used shape feature. A number of works suggested continuous orthogonal basis set for the calculation of image moments [12, 13] such as ZM. This is to overcome problems related to invariant moments such as information redundancy and noise sensitivity. The former implies that each degree of ZM for an image is unique and independent. We have employed ZM as our global shape feature. The application of ZM as shape feature does not requires knowledge of shape boundary. This is also another advantage since not all images have defined boundaries.

Colour feature is one of the most widely used visual features in image retrieval. It is relatively robust to background complication and independent of image size and orientation. Colour histograms are the most common way of describing low-level colour properties of images. A colour histogram is represented by a set of bins, where each bin represents one colour. It is obtained by counting the number of pixels that fall into each bin based on their colour. In the RGB model, colour histograms could be generated either as three independent colour distributions (one for each of the RGB primary colors, namely red, green and blue) or as a joint distribution of all three primary colors. In normalized histograms, each bin represents the percentage of pixels of the corresponding colour found in the image. Thecolour correlogram expresses the probability of finding a pair of colors within a predefined distance of each other. This provides the spatial information without the need for contour extraction. The colour histogram [11]only expresses the colour distribution in the image without regards to any spatial information. Jing Huang in his paper shows that the colour correlogram significantly outperformed the colour histogram in image retrieval problem. Recent work on CPAM however shows that it outperforms colour correlogram in various image retrieval tasks.

CPAM employ grids of non-overlapping patches similar to PHOG but the pattern is only extracted from image of single level. CPAM feature shows the distribution of quantized colour and grayscale pattern in the images. CPAM feature vector is obtained from the histogram of the pattern distribution in the image.

V. EXPERIMENT AND RESULT

A. Experimental Setup

Experiment is conducted to measure the effectiveness of various chosen image descriptors using manual/automated segmentation. A dataset consisting of 313 marine life images is prepared. The images are taken from 9classesof marine life species which are obtained mainly from Google image search and contributed by Malaysian Department of Marine Park (MDRM). The images have been validated by the marine life specialist from MDRM.The species classes selected for the database are sea cucumber, jelly fish, star fish, marine arthropods, marine fish, sea horse, marine mollusk, marine reptiles, and marine worm.

In the experiment, images from the database are being tested and precision and recall isrecorded. We use the chi-square distance metric given in Eq. (1)as the dissimilarity distance. The distance function *D* shows the dissimilarity using chi-squared function between the N-dimensional feature vector of query image *x* and database image *y*. Lower distance value indicate higher similarity among the two images being compared.

$$D(x,y) = \sum_{i=1}^{N} (x(i) - y(i))^2 / (x(i) + y(i))^2 \quad (1)$$

For each query image, the distance function D is computed for all the images in the database. Ten images from the database are retrieved based on the ten lowest distance value. In the experiment we have chosen 6 different types of feature or image descriptor to be evaluated. The selected features are the pyramid of histogram of oriented gradient (PHOG), Zernike Moment (ZM),Fourier Descriptor (FD), ColourCorrelogram (CC), Coloured Pattern AppearanceModel(CPAM) and Colour Histogram (HIST).

B. Result

The performance of the retrieval is measured based on the average precision and recall rate. The precision and recall rate are computed based on Eq. (2, 3) for each retrieval.

$$\text{Precision rate} \quad P_i = N_i / K \quad (2)$$

$$\text{Recall rate} \quad R_i = N_i / C_i \quad (3)$$

N_i represents the number of retrieved image that belongs to the same category as the query image i, K is the number of images retrieved (K=10 is used in the experiment) andC_i represents the numbers of images in the database that belong to the same category as query image i. The average precision and recall rate are obtained by averaging the precision rate for all the query images in a class used.

Experiment 1 result in Fig. 3 illustrates the comparative results of single feature combined with another feature (shape with colour).Fig. 3demonstratesthat combination of shape and colour prove to have better result than just single feature working together. The best combination is FD-CPAM they are don’t have best retrieval result with alone but when combined they show better results compared to others.

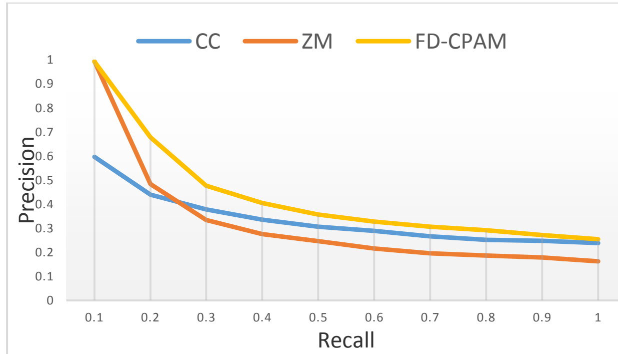


Fig. 3. Results of single features compared to combination

Experiment 2 result in Fig. 4 illustrates the comparative results of all the three automated segmentation. The result is conducted with FD-CPAM as our feature. Fig. 4 proves that our region growing by colour is better in terms of accuracy in retrieval compared to other two.

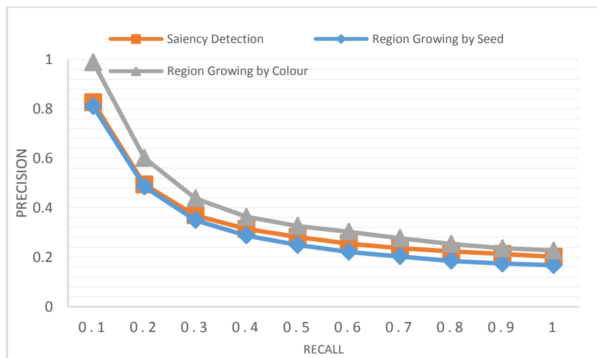


Fig. 4. Retrieval results of different automated segmentation

Experiment 3 result in Fig. 5 illustrates the comparative results of without segmentation and with segmentation (Manual/Automated).The results proves that segmentation eithers it’s manual or automated is better in terms of accuracy in retrieval from without segmentation.

Experimentresult in Fig. (4and 5) clearly illustrates segmentation shows better results compared to without segmentation. Results indicate that automated segmentation has precision and recall values slightly higher to without segmentation, one of the main reasons for it is the automated algorithm could not extract region of interest properly. Comparison shows FD-CPAM givesbetter average precision and recall rate per query image. User can expect to find on average 2 relevant images among the 10 retrieved images for each query image. The result in Fig. 3shows FD-CPAM features exceed the performance of all the other features and combination. Although PHOG is a useful descriptor, the images within similar species category show diverse colour variation and blur makes it hard for PHOG to correctly identify the region of interest. The ZM and FD how better result because they work on segmented images, which help them in correctly identifying the contour of an image. When these techniques are combined with colour they shows much better result than they working alone.

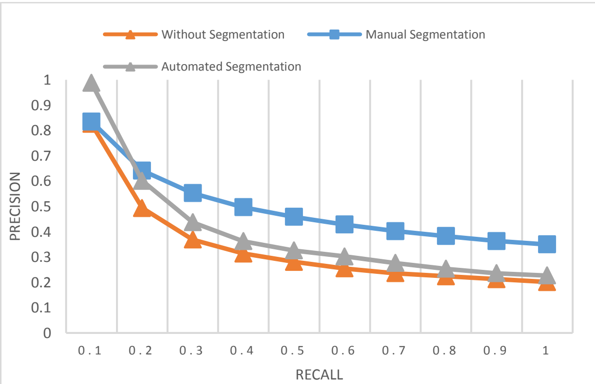


Fig. 5. Retrieval results of without and with segmentation

VI. CONCLUSION

We can conclude from our findings that segmentation helps in the accuracy of the retrieval for the system but manual segmentation is still better than automated segmentation. Our automated segmentation is slightly higher than without segmentation. From the three automated segmentation techniques implemented Region growing by colour shows better average accuracy of retrieval. There are a few reasons which makes it hard for the automated system to work properly, once of them is correctly choosing the region of interest itself. Our algorithm is detecting the brightest region in an image and assigning it as the region of interest which could be not true in few cases. Secondly distortion and diversity in texture and colour makes it hard for the system to work properly for example a fish or sea cucumber could be of multiple colour and system detects similar colour. Our future work will focus on improving the retrieval performance of the CBIR system by enhancing the image features with spatial pattern. We will also investigate other segmenting tools and test which is better for our images and look in to most similar higher priority (MSHP).To overcome this problem GVF (Gradient Flow Vector) is will be tested and evaluated .used which will be discussed later.

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