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Content Based Image Retrieval Using Colour, Texture and KNN

Luke Toroitich Wilson Cheruiyot Kennedy Ogada

School of Computing and Information Technology, Jomo Kenyatta University of Agriculture and Technology,

PO Box 14551-20100, Nakuru, Kenya

Abstract

Image retrieval is increasingly becoming an interesting filed of research as the images that users store and process keep on rising both in number and size especially in digital databases. The images are stored on portable devices which users have used to capture these images. The aim of this research is to solve the issues experienced by users in image retrieval of digital images stored in their devices, ensuring that images requested are retrieved accurately from storage. The images are pre-processed to remove noise and refocus images to enhance mage content. The image retrieval is based on the content (Content Based Image Retrieval) where images are matched in a database based on the subject of the image. In this paper, Corel image database is used with image pre-processing to ensure that image subjects are enhanced. Images are placed in classes and images are retrieved based on the users input. Euclidean distance method is used to determine the nearest objects, thus resulting in the least number of image comparison is made. For KNN algorithm, different values of K will be tested to determine best value for different classes of images. The performance of the design is compared to MATLAB image retrieval system using the same image data set. The results obtained show that the combination of colour, texture and KNN in image retrieval results in shorter computation time as compared to the performance of individual methods.

Keywords: Image retrieval, KNN, clustering, image processing

1. Introduction

Content Based Image Retrieval (CBIR) obtains images from a collection of images using the subjects in the images. Initially, images are stored in digital databases within the storage memories of portable computers or mobile devices. In a CBIR system, the user queries for an image by giving an input image to the system which then is compared to similar images stored in the database. The retrieval is complete when the user is presented with the resultant image that the system deems to be closest to the query image. (Parekh & Limbad, 2014)

An image is comprised of colour, texture and shape, where, these represent the low level features that can be used to describe an image. In this research, image features used for image retrieval focuses on colour and texture.

1.1 Image Characteristics

All images in the digital database are assigned logical memory space, which forms the collection of all images that the user has in collection. The user will first present a query image to the system, in turn; the system checks though the database for the closest matching image. During this search, the feature vectors of the query image and the feature vectors of images in the database are compared. (Muneesawang & Guan, 2011).

Euclidean distance is used to measure the distance between the images, whereby short distances imply similar images and the converse applies. In the experimental set up, all images were made to be one size of 256 x 384 pixels using ImageTuner to enable equal treatment of all images during the image retrieval. This research focuses on colour and texture image features and uses KNN algorithm to determine the nearest neighbours when the value of K is selected.

1.1.1 Image Pre-processing

As a preliminary step in CBIR, it is desired that images subjected to image preprocessing with the aim to remove noise, sharpen the image and focus on the subject. The image preprocessing steps in this research are image resizing and image partitioning. Using ImageTuner tool, all images in the database are resized to 256x384 pixels. This ensures that the pixels of the images are reduced without compromising the image quality. This reduction of image size saves on computation time, which is a significant factor when dealing with databases with large number of images. (Samraj & NazreenBee, 2015). Furthermore the resultant images are partitioned into 6 tiles of dimensions of 2x3 resulting to each partition having dimensions of 128x128 pixels. The colour and texture of these partitions will be extracted and combined to form the feature vector of the image. The 1000 COREL database was used to provide the research images to be stored in the database. In the case of mobile devices, these images were stored in memory sticks or drives. The profile used should have administrator access and rights in order to perform the image retrieval.

1.1.2 Colour

Images in the database are in RGB format which represents colour of the images in Red, Green and Blue. To

perceive with the human eye, it is necessary to convert RGB to HSV format, where H represents Hue, S represents Saturation and V represents Value. Hue (H) is divided into 8 bins, saturation (S) is divided into 3 bins and value (V) is divided into 3 bins. (Duana, Yanga & Yanga, 2011). This forms non uniform intervals of quantization which when the concatenation of this results in an 8x3x3 histogram. The cumulative histogram is used to reduce the number of zeros.

The quantified values of HSV are given by Equation 1:

$$H = \begin{cases} 0if h \in [316,20] \\ 1if h \in [21,40] \\ 2if h \in [41,75] \\ 3if h \in [76,155] \\ 4if h \in [156,190] \\ 5if h \in [191,270] \\ 6if h \in [271,295] \\ 7if h \in [296,315] \end{cases} S = \begin{cases} 0if s \in [0,0.2] \\ 1if s \in [0,2,0.7] \\ 2if s \in [0,7,1] \end{cases} V = \begin{cases} 0if v \in [0,0.2] \\ 1if v \in [0,2,0.7] \\ 2if v \in [0,7,1] \\ 2if v \in [0,7,1] \end{cases}$$
(1)

The conversion from RGB to HSV in MATLAB is provided by the image processing toolbox using the function: rgb2hsv('/inputimage_name').

1.1.3 Texture

Gray Level Co-occurrence Matrix (GLCM) is used to show the spatial distribution of gray levels representing texture of an image (Haralick, Shanmugam & Dinstein, 1973) GLCM denotes how often a pixel occurs in specific relation to another pixel. GLCM can be represented by 4 features: Energy, Correlation, Contrast and Homogeneity where energy is a measure of gray scale image, correlation is the measure of image randomness; contrast is the main diagonal near the moment of inertia and homogeneity which is a measure of the number of local changes in image texture. The four GLCM features are computed for all image partitions during the texture feature representation. The respective values of the four features are shown in Equations 2 to Equation 5.

$$Energy, E = \sum_{x} \sum_{y} P(x, y)^{2}$$
(2)

$$Correlation, C = -\sum_{x} \sum_{y} P(x, y) log P(x, y)$$
(3)

$$Contrast, I = \sum_{x} \sum_{y} (x - y)^{2} P(x, y)$$
(4)

$$Homogeneity, H = \sum_{x} \sum_{y} \frac{1}{1 + (x - y)^{2}} P(x, y)$$
(5)

2. K Near Neighbour

The K-NN algorithm is based on a distance function which helps to classify the input data creating the training data to be used in the training phase of the image retrieval. This system self-adapts the training results as a collection of similar images.

(Chang et al, 2012).

The KNN algorithm works in two phases: the classification stage and the training stage. (Charde & Lokhande, 2013). In the classification phase a given preprocessed image is presented, the colour and texture features are extracted for classification.

The training stage is where system uses the collection of images in classes to perform the image retrieval.

Once the user inputs the query image, the preset value of K will determine the nearest neighbours to the K value, thus classifying images with similar content, creating a classification of the images. These resultant classes form the training data that the CBIR can use to perform the image retrieval.

3. Experimental set up

The general operation of the system is as shown in Figure 1:

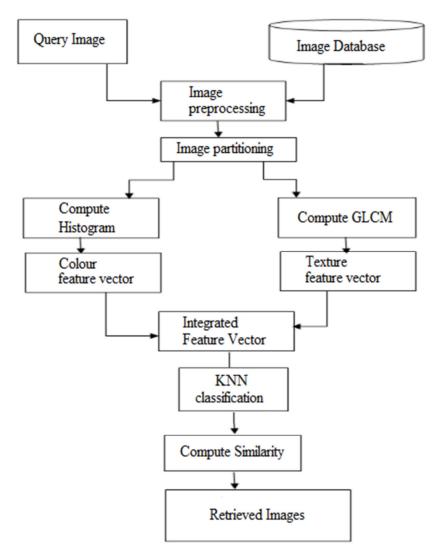


Figure 1: Experimental set up showing the interaction of stages of the image retrieval process

The experiments were run using a Dual Core, 2.4GHz, 6GB RAM computer running on Windows 10 64 bit. ImageTuner version 5.6 Free Edition was used to resize images. The Wang Dataset images provided the research images to be stored in the database.

4. Results and discussion

Experiments conducted yielded test results in two categories: results for image retrieval when HSV and GLCM are used and the results for image retrieval when HSV, GLCM and image partitioning are used. Table 1 shows the findings of precision in retrieving images when HSV and GLCM are applied.

KNN		HSV, GLCM
Classification	HSV & GLCM	& classification
А	0.34	0.41
В	0.21	0.32
С	0.24	0.37
D	0.51	0.66
Е	0.39	0.43
F	0.26	0.39
G	0.81	0.87
н	0.28	0.35
Ι	0.2	0.34
J	0.25	0.31

Table 1 [.]	Precision	values	for	methods applied	(
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These findings when represented in graphical form reveals the difference in precision of image retrieval for the two methods applied. Figure 2 clearly shows the comparison of image retrieval using MATLAB with the proposed methods.

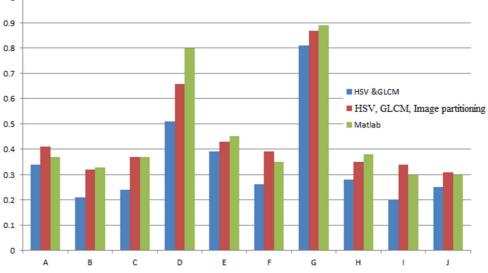


Figure 2: Graphical representation of application of MATLAB in image retrieval in comparison with the precision for HSV & GLCM compared to HSV, GLCM and Image partitioning methods

From the findings, the precision was highest for images whose subject occupied majority of the image space. This is shown by the precision values in classification G. The images in this class were close up images of plants, flowers and portraits. The proposed methods measure up positively to established image retrieval tools like the one in MATLAB. In some instances, the precision for the proposed methods, evidenced by class C. It can also be noted that in cases where images had objects in the background, the proposed system analyzed these objects owing to the image partitioning used in the method. This resulted in increased precision in class D and class I. These results show the potential of the combination of low level features in describing images in vector form then performing the image retrieval based on the vectors. Additionally, the incorporation of a classification algorithm, KNN yielded classification of images based on their similarity. KNN provided the training sets that the system could learn from, which was proved by later experiments.

5. Conclusion

Images that contain one subject occupying the image space show the highest precision in retrieval. The combination of low level features with the capabilities of algorithms enhances image retrieval process. Image

partitioning should be made with consideration that the number of partitions directly affects computation time. Future work could consider the analysis of other algorithms with the proposed methods, choosing the best suited algorithm for given images. Moreover, this research can lead to the development of image retrieval software for the android market and security sector like retina scanning for mobile devices.

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Luke Toroitich is pursuing a Masters degree in Computer systems at JKUAT Nakuru Campus. He is a registered engineer with the Engineers Board of Kenya. He was won the best Science paper in the 7th International Conference: Research and Expo. His interests are in information retrieval, robot vision and machine language

Wilson Cheruiyot is an Associate Professor in Computer Science, a senior lecturer in the School of Computing and Information Technology, at JKUAT Main campus.

Kennedy Ogada is a lecturer at JKUAT Computing department. He has a PhD in Information Technology