CONTENT BASED IMAGE RETRIEVAL USING SPATIAL RELATIONSHIPS BETWEEN DOMINANT COLOURS OF IMAGE SEGMENTS

Hasitha Bimsara Ariyaratne and Koichi Harada
Graduate School of Information Engineering, Hiroshima University, Japan

Keywords: Content Based Image Retrieval, Dominant Colours, Text Index, Spatial Relationships.

Abstract: Content Based Image Retrieval (CBIR) is a quickly evolving area in computer vision and image processing due to the ever increasing number of digital images. Therefore efficient indexing is a vital part in image retrieval systems. Since the ultimate goal of any CBIR system is to simulate the Human visual system (HVS), applying some of the fundamental concepts used in HVS for identifying images such as colour, position size and shape could greatly help enhance the accuracy. Therefore, this research proposes a simple yet effective text based indexing scheme that relies on spatial relationships among dominant colours of image segments. A new connected component labelling approach along with an efficient graph based image segmentation algorithm is used for segment identification. The indexing scheme is capable of identifying both complete and partial image matches. Experiments carried out using different sets of images have yielded promising results, validating the concept's viability for Content Based Image Retrieval.

1 INTRODUCTION

Due to various advancements in digital image capturing, compression, storage and transmission technologies, the number of digital images is increasing rapidly. As a result, efficient image searching and indexing techniques have become a vital aspect in managing this ever-growing image repository. Hence, image analysis, searching and retrieval have become a popular, yet challenging research topic in the area of computer vision and image processing. Conventionally, images were tagged and indexed using text as a Meta descriptor (Chang & Hsu,1992), where images were indexed and retrieved with text descriptions. Most of the commercial and internet based image searching services (i.e. Google Images, Yahoo Image search, Microsoft Bing Image search etc..) still rely on this approach. However, this type of indexing is both labour intensive and error prone, since tagging is usually done manually. Therefore, descriptions are highly subjective and incomplete, for example in some cases critical visual features of an image (i.e. colour, shape, texture etc..) are discarded. Furthermore, text based systems cannot be used in certain application domains where an unknown query image has to be compared with a collection of stored images (i.e. Fingerprint databases, face recognition databases etc.). Therefore, the focus of recent studies in image searching has shifted from conventional text based methods to content based methods. In Content Based Image Retrieval (CBIR) Systems, images are indexed based on visual content of an image such as colour, Texture, Shape and spatial information (Hiremath & Jagadeesh, 2007) instead of user assigned text descriptions.

Content based Image Retrieval systems are widely used by both personal and professional users. Some of the common application areas include forensic sciences (fingerprint, DNA, fibre, hair and bullet fragment matching) (Eakins & Graham,1999), medical imaging (X-Ray, CAT, CT scan images for deceases diagnosis), publishing and engineering (Venters & Cooper, 2001).

Image content can either contain low-level visual attributes such as colour, texture, shape or high-level visual objects such as people, vehicles and buildings. A visual content descriptor is a feature that can be used to extract and store these visual characteristics.

Colour is one of the most prominent visual descriptors used in image retrieval. Colour Histogram is a conventional colour based approach that provide a reasonable accuracy for most CBIR

Bimsara Ariyaratne H. and Harada K. (2010).
CONTENT BASED IMAGE RETRIEVAL USING SPATIAL RELATIONSHIPS BETWEEN DOMINANT COLOURS OF IMAGE SEGMENTS.
In *Proceedings of the International Conference on Computer Vision Theory and Applications*, pages 184-189

applications (Swain & Ballard, 1991), however the lack of spatial features reduces its discriminative power. As a solution, techniques like extended histograms, augmented histograms (Chen & Wong, 1999) and colour correlograms (Huang et al., 1997) were introduced. Even though these new methods incorporate spatial relationships between colours, they still compute a statistical generalization of colour relations, which may not depict the actual relationships. Hence they perform poorly when partial images are concerned.

However, colour alone does not have a very strong discriminative power to capture all the facets of an image; therefore additional descriptors are needed to enhance the accuracy of search results. Psychological experiments have shown that the Human Visual System (HVS) cognizes the world in terms of high-level objects and their spatial relationships, the 'object-ontology' of the HVS can be classified as follows (Liu et al., 2007):

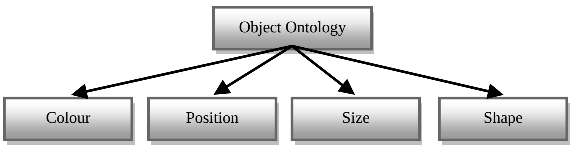

Figure 1: Object ontology.

Since emulating the HVS is the ultimate goal of any image processing technique, representing images using above descriptors can greatly enhance the efficiency of CBIR as well. Due to the complexities of shape based calculations, remaining three descriptors, namely colour, position and size were adopted as the main content descriptors in this research.

The main focus of this research was to implement a new indexing scheme that can capture spatial relationships of significant image segments of an image based on their dominant colours. Remainder of this paper is structured as follows: Section 2 and 3 discusses about colour systems and the importance of using dominant colours, followed by a brief introduction to the image segmentation algorithm used in this research. Section 5 explains the process of creating a pallet of dominant colours followed by an outline of the newly proposed connected component labelling algorithm. Sections 7 and 8 provide an overview of the implementation details and experimental results.

2 COLOUR SPACES

A colour space provides the ability to specify, create and visualise colours; it is an abstract mathematical model describing how colours can be represented as points in a 3D space.

Many different colour systems are used to represent colours in digital images, the most widely used model is RGB, however, HSL/V, CMY/K and CIELab (International Commission on Illumination's Lightness, a, b colour component model) are also used depending on different applications and requirements.

Despite having so many different colour models, only a handful of them such as CIELab have a perceptually uniform colour space. In such a colour space, a linear change of data results in a linearly perceived colour change; in other words the Euclidian distance between two colours should represent the colour difference as perceived by the human vision system (Shih et at., 2001).

Since this research focused on processing images based on a reduced colour palette (dominant colours), colour approximation was a vital part. For this reason CIELab colour space was used for better accuracy in calculating dominant colours.

3 DOMINANT COLOURS

Modern images contain millions of colours; but if this number can be decreased to tens or hundreds without losing a significant amount of the detail, then both the storage size and computational power required for processing images can be drastically reduced.

In a typical image, most of the colours are simply shades of a few basic colours. These basic colours dominate the whole image while capturing the essential details, hence called dominant colours. Therefore, by processing an image with regard to these dominant colours can help reduce the processing and storage requirements without significantly reducing the discriminative power of the image. The process of deriving the dominant colours is discussed in section 5.

4 IMAGE SEGMENTATION

Since this study focused on building an image index based on objects and their spatial/colour relationships, segmenting the image was a major task. There are many image segmentation algorithms available today; among them Histogram based methods, Edge detection methods, Region growing methods and Graph based methods take prominence. A recent study carried out on evaluating various image segmentation algorithms has suggested a particular Graph Based Image Segmentation Algorithm (ISA) to be very efficient (Pantofaru et al., 2005)(Felzenszwalb et al., 2004); therefore this approach was adopted for the image segmentation step of our research. The algorithm builds up an undirected graph where

- vertices = pixels
- edges = connections between neighbouring pixels with a weight
- weight = similarity of the vertices connected by an edge

The algorithm uses a minimum spanning tree approach to segment the pixels in to clusters depending on the weights associated with edges.

This algorithm has two user changeable parameters σ and k. Where σ is the standard deviation of the Gaussian filter used to smooth the image in order to eliminate some of the compression artefacts before computing the edge weights. K is a variable in the threshold function that controls the degree of the difference between two components must vary in order for there to be evidence of a boundary between them. The constant k therefore can be used to specify the maximum and minimum size of a component.

5 DOMINANT COLOUR PALLET

The colour pallet used in this research contains 42 colours. Since CIELab is a perceptually uniform colour space, selecting points that are equally distanced from each other provide a uniformly distributed colour pallet. For simplicity, the space was partitioned into a cubic grid, thereafter CIELab colour values corresponding to vertices with a valid RGB values were selected. Even though points of a cube don't lie at equal distances to one another, experiments have yielded good results on the sparsity of the colours.

Further experiments were carried out on a sample image set to obtain an optimized colour palette. First, the images were segmented with the ISA; afterwards all segments were converted in to dominant colours using different colour pallets containing different number of colours. Finally the number of colours per image segment was counted for each pallet. The pallet with the maximum number of colours and minimum number of colours per segment was chosen as the optimal palette. Figure 2 shows the experiment results:

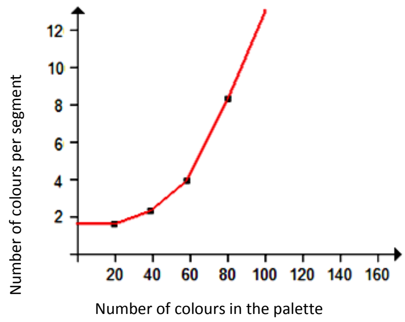

Figure 2: Colour palette size vs. segmentation accuracy.

6 CONNECTED COMPONENT LABELLING

An image segmentation algorithm only splits an image into multiple segments, but it does not help identify individual objects nor extract essential high level information about segments. Therefore, in order to extract these additional information, a component labelling algorithm was used.

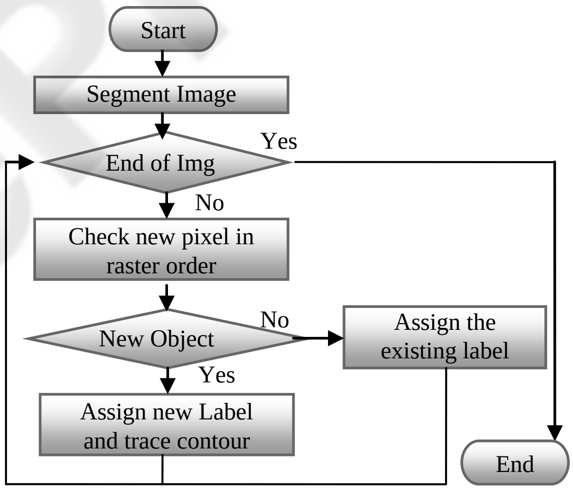

Figure 3: Flow chart of the proposed CCL algorithm.

Most of the Connected component labelling methods in use today are for binary and grey scale images (Wu et al., 2009), but this research proposes a colour CCL algorithm based on image segmentation. Figure 3 lists the flow chart of the proposed CCL algorithm.

The first step of the algorithm segments the image. This segmented image has all segments coloured with a random but a unique colour, since colour processing is not a part of the ISA. Then, the image is scanned from top to bottom and left to right, for each line in raster order. When a new object (identified by a colour change) is encountered, the algorithm assigns a new label (the lowest unassigned numerical value) and start tracing along the contour in the clockwise direction till it reaches the starting point of the trace; while tracing, all the pixels of that contour are given the same label.

7 OVERALL SYSTEM

This section describes the overall design of the system and how the techniques discussed previously are applied in indexing an image. Figure 4 represents the overall image processing module:

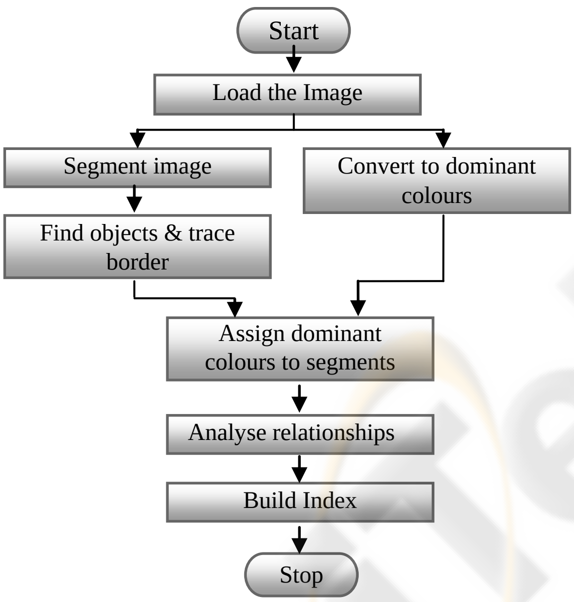

Figure 4: Flow chart of the image processing module.

Segment Image: Segments the image using the ISA discussed previously.
Convert to Dominant Colours: converts a copy of the image to dominant colours.
Find Objects and Trace Border: executed with help from the proposed CCL algorithm.
Assign Dominant Colours to the Segments: using the dominant colour image as a reference, all the segments derived by the ISA are assigned a dominant colour. For each segment all the corresponding pixel values in the dominant colour image are scanned, the colour which has the highest pixel count is then assigned as the dominant colour of the corresponding segment.
Analyse Relationships: In order to find the surrounding objects of a given object, the contour is traced to search for adjoining colour regions. While tracing the contour, adjoining object IDs, and the number of pixels along the shared boundary are stored. Relationship between adjoining objects is derived by:

$$\text{Relationship} = \frac{\text{Pixels of the common boundary}}{\text{Length of the contour}} \quad (1)$$

This relationship value is stored as an attribute in the final index as illustrated in Figure 5 to represent the spatial relationships between adjoining image segments.
Build Index: Finally, the index is constructed with the colour of the object followed by its relationships to the colours of surrounding objects in a formatted string as shown in Figure 5.

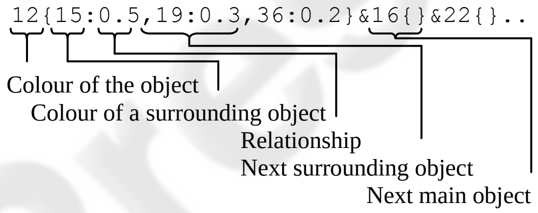

Figure 5: A sample string index.

Figure 6 illustrates a high-level example of how an image is segmented and indexed. The right most section of the figure shows how the index is represented in relation to the dark red colour door of the car.

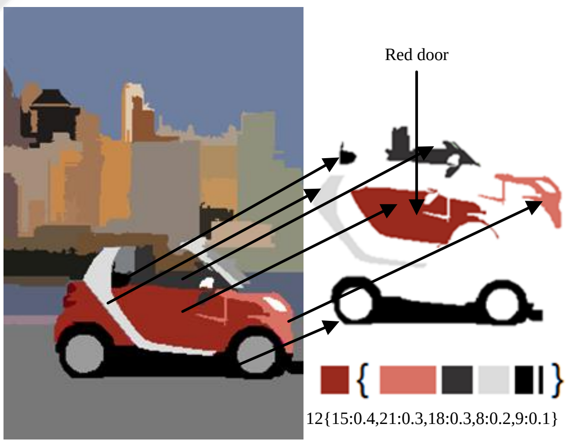

Figure 6: An illustration of how neighbouring image segments are processed in relation to a particular segment.

8 IMAGE RETRIEVAL AND EXPERIMENTAL RESULTS

This research mainly focused on implementing a new indexing scheme for searching and retrieving images based on a complete or a partial query image. As a result a new string index similar to the representation illustrated in Fig 6 was introduced.

Once a query image is given, an index is generated for that image as detailed in section 7. The generated index is then compared against other indices in the database for number of matched image segments. An image segment is considered equal or matched if the string representation of the considered segment (the dominant colour followed by surrounding dominant colours and their relationships) are matched. Image(s) with the highest matching accuracy is(are) retrieved as the query result(s).

$$\text{MatchingAccuracy} = \frac{\text{No:OfMatchedImgSegments}}{\text{TotalNo:OfSegmentsInTheImg}} \quad (2)$$

$$\text{QueryImageSize} = \frac{\text{No:OfSegmentsInThePartialImg}}{\text{No:OfSegmentsInTheCompleteImg}} \quad (3)$$

The proposed system was tested using three different image sets:

1. 50 randomly selected images searched from google image search
2. Screenshots taken from "The simpsons" cartoon series.
3. 60 images from Corel Image database which was pre classified by 30 human subjects.

Experimental results have shown that matching accuracy for unrelated images was averaging around 0.2 or below. Tables 1 and 2 lists the results carried out on the first image set with different values for σ. From these results it is evident that this technique could produce satisfactory results for partial image queries if the query image contained at least 50% of the original content.

Figure 7: Sample images of Set 1.

Table 1: Search results for a set of 50 randomly selected Google Images (σ = 0.6, k max = 1/150th of the image k min = 1/300th of the image).

Query image size	Matching accuracy
100%	~1.00
75% ~ 100%	0.45~0.55
50% ~ 75%	0.30 ~ 0.45
25% ~ 50%	0.10 ~ 0.30

Table 2: Search results for a set of 50 randomly selected Google images (σ = 0.3, k max = 1/150th of the image, k min = 1/300th of the image).

Query image size/content	Matching accuracy
100%	~1.00
75% ~ 100%	0.35~0.50
50% ~ 75%	0.20 ~ 0.35
25% ~ 50%	0 ~ 0.30

The disparity in the results of Table 1 and 2 indicates that the matching accuracy heavily depends on the Image Segmentation Algorithm (ISA) and its parameters. Table 3 lists the results carried out on the second dataset. Since cartoon images are relatively simple and have a uniform colour distribution, the image segmentation algorithm performs well. As a result matching accuracy is also higher. This is yet another indication of the proposed studies dependability on the image segmentation algorithm.

Figure 8: Sample images of set 2.

Table 3: Search results for cartoon images (σ = 0.6, k max = 1/150th of the image k min = 1/300th of the image).

Query image size/content	Matching accuracy
100%	1.00
75% ~ 100%	0.55~0.65
50% ~ 75%	0.30 ~ 0.55
25% ~ 50%	0.10 ~ 0.30

We also tested the system for image classification ability using 60 pre-classified images. The test images had somewhat uniform colour relationships within each group of images of. The Classification accuracy is calculated for each category N by averaging the matching accuracy of each image against all the n number of images in the category.

Figure 9: Sample images of set 3.

$$\text{ClassificationAcc}_N = \frac{\sum \text{MatchingAccWith}_n}{n} \quad (4)$$

Table 4: Image classification accuracy (σ = 0.3, k max = 1/150th of the image k min = 1/300th of the image).

Category	Classification accuracy
1	0.75
2	0.65
3	0.80
4	0.40
5	0.50
6	1.00
Overall	0.68

Even though image classification was not an objective of the original research project, experimental results suggest that it has the potential to classify images when there are common colour relationships within groups of images.

9 FUTURE ENHANCEMENTS

As discussed earlier, performance of the ISA is a main limitation; therefore a better ISA can improve the overall accuracy. The indexing scheme proposed in this study is relatively simple, even though the results are promising, incorporating additional parameters can improve the efficiency even further. Optimizing the colour palette generation and incorporating newer standards of CIELab colour space may also yield better results.

10 CONCLUSIONS

The aim of this study was to explore the possibilities of using high-level objects (image segments) with dominant colours and spatial relationships to enhance the efficiency of CBIR, especially with regard to partial image matching capabilities. Experimental results are a strong indication to the viability of this approach.

REFERENCES

Chang,S. & Hsu,A. (1992). "Image information systems: where do we go from here?". IEEE Transaction on Knowledge and Data Engineering, Vol.5, No.5, 431-442.

Chen, Y. & Wong, E. (1999). ”Augmented image histogram for image and video similarity search”, Proceedings of Society of Photographic Instrumentation Engineers conference on Storage and Retrieval for Image and Video Databases.

Eakins,J. & Graham,M.(1999).”Content-based Image Retrieval”,University of Northumbria at Newcastle, Library and Information Briefings,Bulletin Board for Libraries Journal.

Felzenszwalb, P. & Huttenlocher, D. (2004). ”Efficient Graph-Based Image Segmentation”, International Journal of Computer Vision, 59, 2, 167-181.

Hiremath, P. & Jagadeesh, P. (2007). "Content Based Image Retrieval Using Color, Texture and Shape Features". Proceedings of the 15th International Conference on Advanced Computing and Communications, 780-784.

Huang, J. Kumar, S. Mitra,M. Zhu,W. Zabih, R. (1997). ”Image indexing using color correlograms”, IEEE Computer Society conference on Computer Vision and Pattern Recognition,762-768.

Liu, Y. Zhang, D. Lu, G. Ma, W. (2007). ”A survey of contentbased image retrieval with high-level semantics”, Proceedings of Pattern Recognition, 40, 262-282.

Pantofaru, C. & Hebert, M. (2005). “A Comparison of Image Segmentation Algorithms,”. Technical report, Robotics Institute of Carnegie Mellon University.

Shih, T. Huang, J. Wang, C. Hung, J. Kao, C. (2001). "An Intelligent Content-based Image Retrieval System Based on Colour". Proceedings of National Science Council, 25, 4, 232-243.

Swain, M. & Ballard, D. (1991) ”Color indexing”, International Journal of Computer Vision, 7, 1, 1132.

Venters, C. & Cooper, M. (2001). ”A Review of Content-Based Image Retrieval Systems”, Joint Information Systems Committee. England: JISC.

Wu, K. Otoo, E. Suzuki, K. (2009). ”Optimizing two-pass connected-component labelling algorithms”, Proceedings of Pattern Analysis and Applications, 12, 117-135.