# IMAGE SEARCH USING SIMILARITY MEASURES BASED ON CIRCULAR SECTORS

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***ABSTRACT***

*With growing number of stored image data, image search and image similarity problem become more and more important. The answer can be solved by Content-Based Image Retrieval systems. This paper deals with an image search using similarity measures based on circular sectors method. The method is inspired by human eye functionality. The main contribution of the paper is a modified method that increases accuracy for about 8% in comparison with original approach. Here proposed method has used HSB colour model and median function for feature extraction. The original approach uses RGB colour model with mean function. Implemented method was validated on 10 image categories where overall average precision was 67%.*

***KEYWORDS***

*CBIR, circular sectors, cross-validation, image features, image processing, image similarity, optimization*

## 1. INTRODUCTION

Nowadays, the amount of transmitted image data through internet is every day still growing and due to this fact digital image databases are filled with new terabytes of images. In order to search and manage this data, there is strong need to index or categorize these images using proper system. Searching images on the basis of similarity can be used in medicine, arts, industry [1], security, military and many other areas [2].

This work deals with an image categorization and search on the basis of content. Systems that provide this functionality are called Content-Based Image Retrieval (CBIR) [3]. These systems search huge image databases, where for every image the special signature is created. The signature is used for comparing with image we want to categorize. In our approach we improved circular sector method introduced in [4] and we increased accuracy for about 8%.

CBIR systems usually use visual image properties like colour, texture and shape for creating feature vectors that are saved in to the database. Visual image properties are compared by using similarity measurements (Euclidean metrics, Manhattan metrics) and according to the value of

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measurements, images are compared or searched in database. CBIR systems use several methods for the computing of feature vectors. Methods can be based on local or global feature extraction or can be based on colour coherence vectors [5], colour moments [6], circular sectors [4] or Gabor filters [6]. The CBIR system architecture is depicted in Figure. 1.

The main contribution of the paper is method that modifies original approach [4]. This approach uses circular sectors method that is inspired by human eye functionality. We achieved higher accuracy for about 8% when compared with [4]. We conducted parameter optimizations using cross validation process and machine learning [19] to find optimal learning algorithm and its configuration. Our approach uses different types of circular sector features where we used HSB colour model with median function instead of RGB colour model with mean function for feature computation.

The rest of this paper is organized as follows: The second section describes related work with focus on CBIR systems. Section 3 describes circular sector method. In section 4 method modification is described. Image data sets are described in section 5. The section 6 describes optimization of parameters. Results are discussed in section 7 and section 8 concludes this paper.

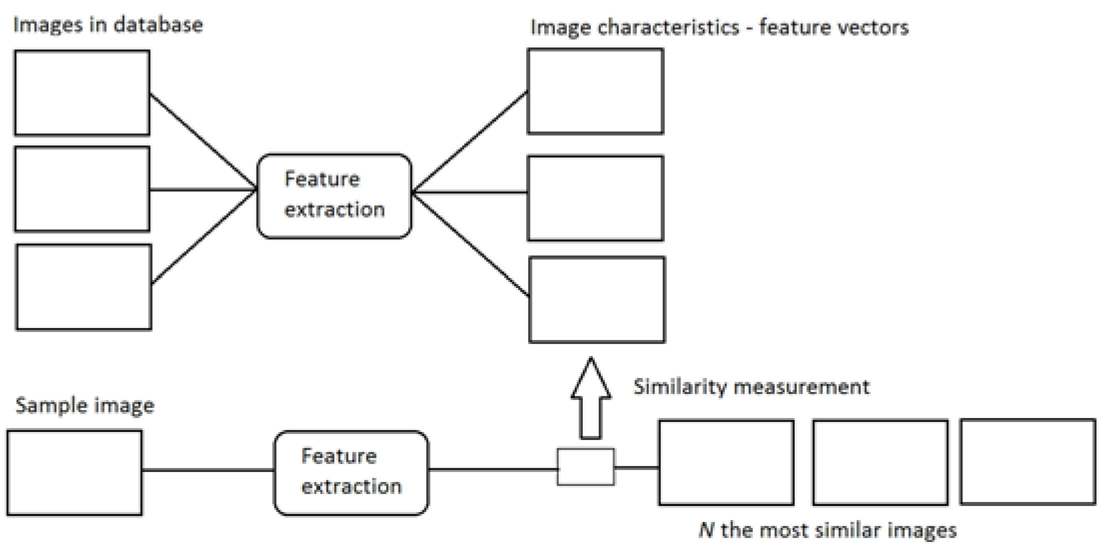


Figure 1. Content base image retrieval system architecture.

## 2. RELATED WORK

Until today many content base image retrieval systems have been created [3]. We present several leading systems in this chapter. For example QBIC system from IBM has been used for many further work dealing with CBIR. Another leading systems are visualSeek or Netra [4]. From these systems many following system have been derived [7], [8] and [9].

There are many works dealing with different image features. Histogram intersection computation has been used to compare images in [10]. Cumulative histograms were described in [11] and spatial matching with colour histograms were described in [12]. In [13] and [14] is proven that colour features are very suitable for similarity measurements.

We also described method based on dominant colours in [15] for measuring image similarity and in [16] system for automatic image labelling using similarity measures is described. In [17] video scenes were segmented using similarity measures.

## 3. CIRCULAR SECTORS METHOD

This method has been described in [4] and it is based on human eye principle. The human eye firstly focuses on the center of image and then goes to the edges of image. The method creates special image features that are obtained from image. Firstly, the center of image is determined and then image is divided in to concentric circles $Ci$, where $i$ is number of circle. Then every circle is divided to sectors $Si$, where $Si = 8\ Ci$. In this case, seven circles are chosen and 252 sectors in whole image are created (see Figure 2 - left). Due to the fact that we use RGB color model with 3 channels, we need to create $3 \cdot 252 = 756$ sectors. The next step is to compute mean value in every sector (see Figure 2 - right). So the image feature is computed as mean value of defined sector. When this method is applied on input image, output feature vector containing mean values of all sectors is computed.

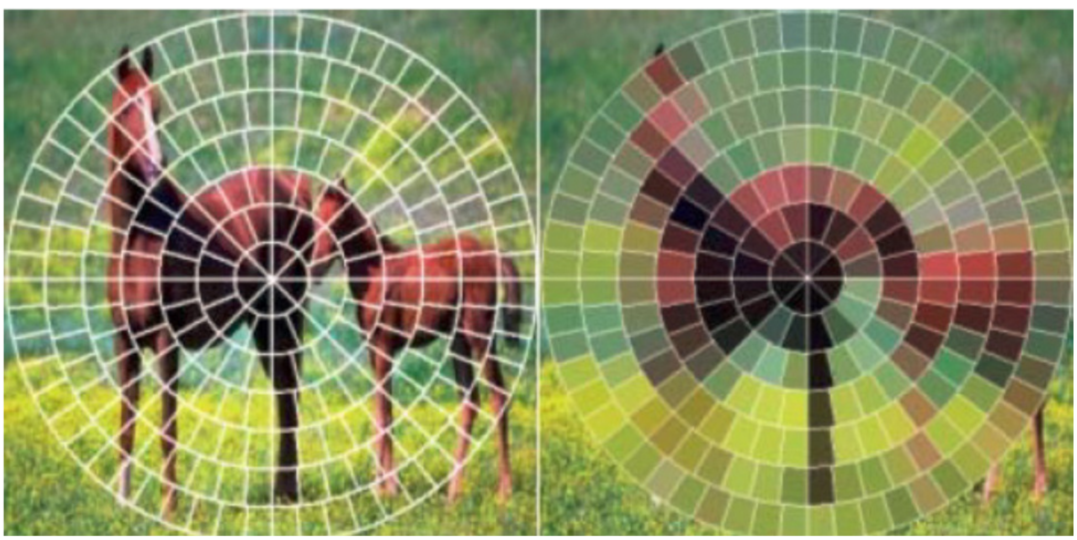

Figure 2. Circular sectors in the image (left), average colour values in each sector (right) [4].

To make this method rotation-invariant, the mean values of sectors are sorted in every circle. Figure 3 shows that sorted sectors are similar when using normal or rotated image.

## 4. METHOD MODIFICATION

In originally described method authors used for feature extraction RGB channels and mean value computation. We decided to create new image features using median function and using HSB colour model. The comparison between these new features and previously used features will be described in chapter 6. Our implementation of algorithm has been created in JAVA programming language according to previous work [4] with our new modifications.

### 4.1 Median

The mean colour value of sector cannot exactly determine the distribution of pixel values (e.g. if image contains a little noise). We modify previous method with using median values instead of mean values.

### 4.2 HSB Colour Model

For human perception the HSB model suits better than RGB model. HSB is an abbreviation of Hue, Saturation, and Brightness. This model use the cylindrical-coordinate representations of values in an RGB model. We use the HSB model instead of RGB colour model.

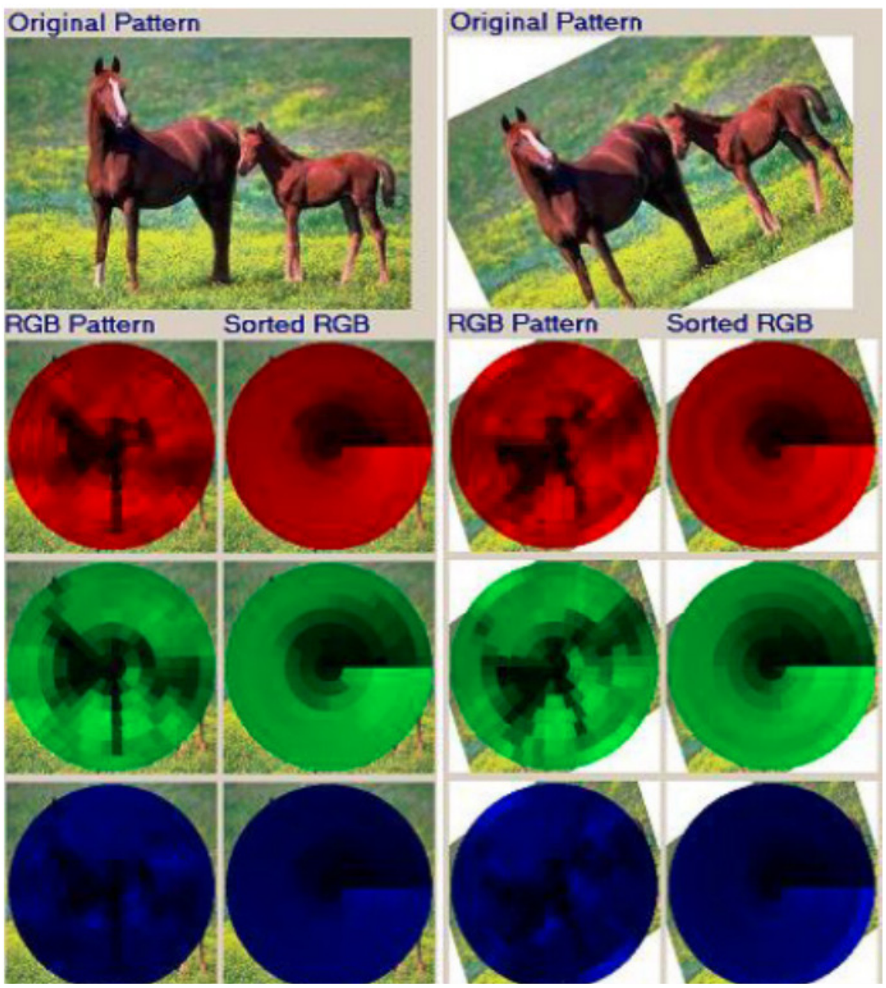


Figure 3. Original image with original and sorted sector values (left), 30° rotated image with original and sorted sector values [4].

## 5. DATA SETS

In this work we used same image data set as authors that described original circular sector method [4]. This data set is available to download from [20]. Data set consists of 10 categories (ancient, beach, bus, dinosaur, elephant, flower, food, horse, mountain, natives) where every category contains 100 images. We have 1000 images overall. The images have dimension 354x256 pixels. The example of used images is shown in Figure 4.

Figure 4. Example of used images

## 6. PARAMETERS OPTIMIZATION

There are many options how to extract features from image. For example dimensions of image, the number of circles for creating sectors. Features can also be extracted using RGB or HSB colour model or computing median or mean value. We chose nine variants that we wanted to compare. For every variant, features were generated to format suitable for RapidMiner [21] data mining tool. This tool contains many machine learning algorithms (e.g. algorithms of artificial intelligence, optimization algorithms). We used cross-validation process [19] (see Figure 5) that computes accuracy for every variant. The cross validation process used SVM (Support Vector Machines) algorithm [18] of artificial intelligence. The SVM algorithm had these parameters:

- SVM type: C-SVC
- Kernel type: linear
- C: 1.1
- Epsilon: 0.001

The results of cross-validation process for every variant is shown in Table 1. It shows that HSB colour model has higher accuracy than RGB model and also median function achieves higher accuracy than mean function. The best achieved accuracy is 75.6% for image with 400x400 pixels dimensions, with 7 circles and HSB model where features are computed using median function. It also shows that our approach that uses HSB model with median function has higher accuracy (75.6%) in comparison with original approach [4] that uses RGB model with mean function. Our modified method achieves for about 8% higher accuracy.

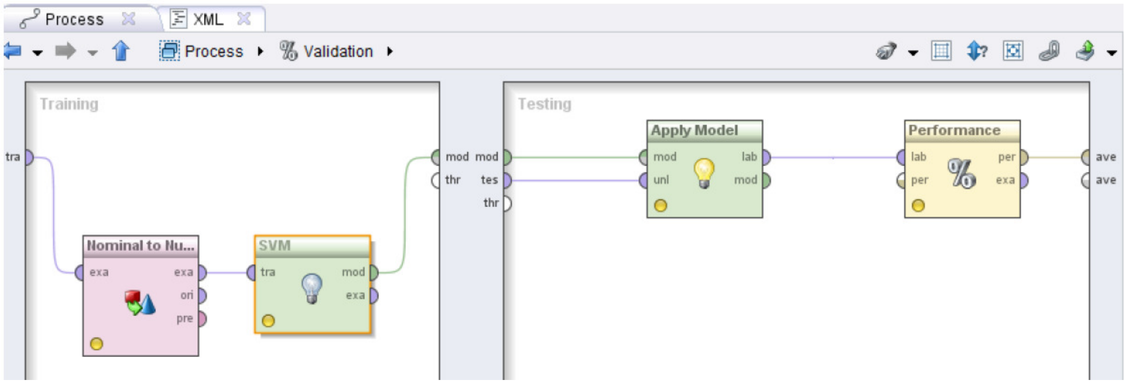


Figure 1. The scheme of cross validation process in RapidMiner tool.

Table 1. Selected variants and their accuracy of classification.

| Dimensions | Circles | RGB mean | RGB median | HSB mean | HSB median |
|---|---|---|---|---|---|
| 200x200 | 3 | 64.3 % | 66.0 % | 71.0 % | 71.5 % |
| 200x200 | 5 | 65.6 % | 67.3 % | 72.3 % | 72.9 % |
| 200x200 | 7 | 68.1 % | 70.5 % | 72.6 % | 74.8 % |
| 300x300 | 3 | 65.0 % | 65.6 % | 70.6 % | 72.4 % |
| 300x300 | 5 | 68.6 % | 68.9 % | 72.8 % | 72.0 % |
| 300x300 | 7 | 67.2 % | 71.3 % | 72.9 % | 74.1 % |
| 400x400 | 3 | 64.4 % | 65.5 % | 71.1 % | 72.2 % |
| 400x400 | 5 | 68.6 % | 69.0 % | 72.7 % | 72.4 % |
| 400x400 | 7 | 67.6 % | 70.8 % | 73.2 % | **75.6 %** |

Table 2 shows confusion matrix for every image category. The best precision was achieved with dinosaur category (97.09%) and the lowest precision was achieved category ancient (53.45%).

Table 2. Confusion matrix for parameters (dimensions 400x400, circles 7, HSB median).

| | | **Label (real values)** | | | | | | | | | | **Prec. [%]** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | ancient | beach | bus | dinosaur | elephant | flower | food | horse | mountain | natives | |
| **Prediction** | ancient | 62 | 16 | 0 | 0 | 7 | 0 | 3 | 2 | 12 | 14 | 53.45 |
| | beach | 11 | 62 | 3 | 0 | 1 | 0 | 5 | 2 | 20 | 2 | 58.49 |
| | bus | 2 | 2 | 83 | 0 | 0 | 3 | 3 | 0 | 5 | 1 | 83.84 |
| | dinosaur | 0 | 1 | 0 | 100 | 0 | 0 | 1 | 0 | 0 | 1 | **97.09** |
| | elephant | 8 | 2 | 0 | 0 | 79 | 0 | 1 | 0 | 3 | 6 | 79.80 |
| | flower | 0 | 0 | 4 | 0 | 0 | 88 | 4 | 0 | 0 | 2 | 89.80 |
| | food | 0 | 3 | 4 | 0 | 0 | 7 | 72 | 1 | 2 | 11 | 72.00 |
| | horse | 3 | 1 | 0 | 0 | 1 | 0 | 2 | 93 | 0 | 0 | 93.00 |
| | mountain | 6 | 12 | 4 | 0 | 6 | 2 | 1 | 0 | 57 | 3 | 62.64 |
| | natives | 8 | 1 | 2 | 0 | 6 | 0 | 8 | 2 | 1 | 60 | 68.18 |

# 7. RESULTS

We performed several comparison tests to verify our modified method. For evaluation, we used precision that is computed:

$$P = \frac{N_{\mathrm{TP}}}{N_{\mathrm{TP}} + N_{\mathrm{FP}}}$$

where $N_{\mathrm{TP}}$ is a number of true positive (relevant) images and $N_{\mathrm{FP}}$ is number of false positive (irrelevant) images. Firstly, one pattern image is selected and its feature vector is computed, then this feature vector is compared with the feature vectors of all images from data set. When data set contains 1000 images, the comparison process had to be executed 1000000 times.

Comparison has been done with computing Euclidean and Manhattan metrics

$$d_E(x,y) = \sqrt{\sum_{i=1}^{d}(x_i - y_i)^2}$$

$$d_M(x,y) = \sum_{i=1}^{d}|x_i - y_i|$$

where $d$ is the length of input feature vector and $x$ and $y$ are feature vectors of 2 images that are being compared. For every image, $N$ the most similar images are selected, where we set $N = \{10,\ 25, 50, 100\}$ and the precision is computed for $N$ images. Finally, the overall precision is computed as average of all precisions computed for every image.

Table 3 shows precision of every category (each contains 100 images) using Euclidean metrics and Table 4 shows precision using Manhattan metrics. Overall average precision is shown in Table 5. The best achived precision was 67.23% for $N = 10$ with using Manhattan metrics.

Table 3. Precision of every category using Euclidean metrics.

| $N$ | Ancient [%] | Mountain [%] | Bus [%] | Dinosaur [%] | Elephant [%] | Food [%] | Horse [%] | Beach [%] | Flowers [%] | Natives [%] |
|---|---|---|---|---|---|---|---|---|---|---|
| 10 | 44.3 | 51.7 | 62.5 | **97.7** | 65.2 | 56.9 | 89.8 | 53.9 | 72.2 | 43.3 |
| 25 | 33.48 | 44.44 | 52 | 97.28 | 52.48 | 44.68 | 82.24 | 44.04 | 59.16 | 33.92 |
| 50 | 30.004 | 40.58 | 42.4 | 94.8 | 44.72 | 36.54 | 73.04 | 37.56 | 43.96 | 28.52 |
| 100 | 25.73 | 34.26 | 34 | 80.44 | 37.76 | 28.79 | 56.24 | 31.51 | 29.95 | 24.81 |

Table 4. Precision of every category using Manhattan metrics.

| $N$ | Ancient [%] | Mountain [%] | Bus [%] | Dinosaur [%] | Elephant [%] | Food [%] | Horse [%] | Beach [%] | Flowers [%] | Natives [%] |
|---|---|---|---|---|---|---|---|---|---|---|
| 10 | 51 | 52 | 63.9 | **99.7** | 66 | 66 | 92.1 | 50.3 | 79.2 | 52.1 |
| 25 | 41.76 | 44.72 | 54.24 | 99.52 | 53.64 | 58 | 86.96 | 43.04 | 67.8 | 43.88 |
| 50 | 33.76 | 39.66 | 45.22 | 98.84 | 44.74 | 48.54 | 79.18 | 37.04 | 51.82 | 37.8 |
| 100 | 28.59 | 34.04 | 36.63 | 91.81 | 36.98 | 37.01 | 62.42 | 32.28 | 36.55 | 32.46 |

Table 5. Overall average precision

| $N$ | Euclidean distance | Manhattan distance |
|---|---|---|
| 10 | 63.75 % | **67.23 %** |
| 25 | 54.57 % | 59.36 % |
| 50 | 47.22 % | 51.66 % |
| 100 | 38.25 % | 42.74 % |

All computations were performed on computer with processor Intel Core i5 2.5 GHz and with 4GB of RAM memory. The computing of feature vector for all images took 1 minute and 9 seconds. To find and compare input pattern image with all image feature vectors (1000) took approximately 2 seconds.

The results of searching pattern image (see Figure 6) for horse category are shown in Figure 7. When pattern image is rotated to left by 90°, the results (see Figure 8) contain 4 incorrectly selected images.

Figure 6. Pattern image for horse category.


Figure 7. First 10 the most similar images of horse pattern image.


Figure 8. First 10 the most similar images of horse pattern image rotated about 90°

## 8. CONCLUSION

The main contribution of this paper is a method that increases accuracy in CBIR systems for about 8% in comparison with original approach [4]. The origin achieved accuracy was 67.6%. We are currently able to achieve 75.6% accuracy with using the same image data set. We tried to find suitable parameters for circular sectors method. We selected the method because it is inspired by human eye functionality. We conducted parameters optimization using cross validation process with algorithms of artificial intelligence, where we found that HSB colour model and median function for feature computation achieve better result than original approach using RGB colour model with mean function for feature computation. For testing we used 1000 images from 10 categories. The best result of average precision was 67.23% with using Manhattan metrics. The average time for image comparison with database was 2 seconds on common computer.

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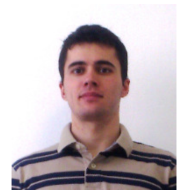

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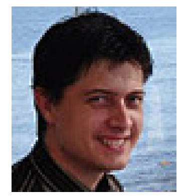

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