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Image Similarity Using

Color Histograms

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Image similarity using color histograms

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Abstract

In this thesis an evaluation of multiple methods of image classification is presented. We explore the application of color spaces and several histogram distance calculation algorithms to achieve a classification system that's able to determine whether an image belongs to a certain set with a specific theme.

For this thesis a C++ program has been build using OpenCV to extract color information from images in either RGB or HSV color space, then this information is used to calculate similarity between images using one of the following algorithms: Euclidian distance, Intersection distance, Quadratic cross distance and Earth's mover's distance. Precision and recall are then used to evaluate the combination of the chosen colorspace and algorithm.

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Chapter 1

Introduction

We currently live in a world where information seems to be highly accessible. This is caused by the paradigm-shift caused by the introduction of the Internet. The science of information retrieval has become a much more important science since then. How to manage, store and retrieve large scale imagery data is still a major challenge in computer science [1] [19]. The improvement in hardware and availability of bandwidth has created new possibilities for sharing information in the form of multimedia. Although textual based information retrieval has been explored thoroughly, Multimedia based information retrieval is a branch of information retrieval that has many unexplored fields.

This paper focuses on images, a multimedia object that is widely used throughout the internet. Retrieval of images from the internet is mostly done through search engines. These engines usually ignore the actual content of the image and use certain information from the context of the image, such as file-name and HTML-tags. Content Based Image Retrieval (CBIR) studies the retrieval process of images based the content of images. CBIR uses methods that analyse the actual content of the image such as color frequency, shapes, texture and many more various features. There have been many different approaches on how to deal with these features. The focus of this thesis is to explore the color features and the different methods that have been developed.

1.1 Personal motivation

I chose this subject because I am interested in CBIR. CBIR is a relatively new science which might implicate large unexplored areas for research. I find it interesting to see the many different features that can be extracted from an image to give a certain meaning to an image, but also how they are weighted against each other. This type of research makes you question how a human evaluates an image and how an algorithm could simulate

that evaluation process.

1.2 Our goal

In this thesis we to compare four different methods of calculating the distance or similarity between two histograms; In combination with two different color spaces. The algorithms we use are: the Euclidean distance, the Intersection Distance, the Quadratic Cross Distance and the Earth Mover's Distance. The color spaces used are RGB and HSV. We try to find out which algorithm and which color space is most suited for image retrieval using color histograms.

1.3 Thesis Overview

First we address some of the more recent works in the field of image retrieval systems in chapter 3. Then we discuss the different color spaces and their uses in chapter 4. In chapter 5 we discuss how the application that was build for this thesis and algorithms work. We then try to use this system to classify two different image datasets in chapter 6. And finally we make a conclusion based on the results of the classification process in chapter 7.

Chapter 2

Definitions

Color Space, Quadratic Cross Distance, Earth Mover's Distance, RGB, HSV, Histogram, Image-similarity, CBIR, Image Classification, Corel, MIRFLICKR.

Chapter 3

Recent related work

There has been significant prior research in the field of image retrieval [22]. Below we discuss some of the more recent work in this field.

3.0.1 Vedran Ljubovic, Haris Supic

Vedran Ljubovic and Haris Supic propose a compact color descriptor for image retrieval [12]. They describe a method for image retrieval that outperforms other methods in terms of memory usage. Their paper contributes to the use of HSL colorspace and the use of the Matsushita distance for similarity measurement.

3.0.2 Koen E. A. van de Sande and Theo Gevers and Cees G. M. Snoek

In their paper "Evaluation of Color Descriptors for Object and Scene Recognition" van de Sande et al. study the invariance properties and the distinctiveness of color descriptors in a structured way [24]. They show that invariance to light intensity and light color changes affects the object and scene category classification.

3.0.3 Yong-Hwan Lee and Sang-Burm Rhee

Lee et al. describe a new and efficient method for image retrieval [9]. They do this by creating an image descriptor that uses a combination of color features based on wavelet color-spatial information and texture features based on the Gabor wavelet texture. Their result show an improvement in retrieval effectiveness, specifically in multi-resolution image searches. However their method, in comparison to similar methods, is very heavy in memory usage and computing time.

3.0.4 Junfeng Wu, Zhiyang Li ,Yujie Xu, Cahngqing Ji, Yuanyuan Li, Xufeng Xing

In order to make color histograms more distinguishable, Wu et al. propose a method by dividing images into blocks [28]. By weighting each block they create a color histogram for an image by combining the color histograms for each block. Their results show an increase efficiency and accuracy of image retrieval for "user-interested" images.

3.0.5 Leonardo Trujillo, Pierrick Legrand, Gustavo Olague

Using a genetic algorithm, Trujillo et al. show descriptors based on the Hlder exponent can be improved in the descriptor's dimensionality. The descriptor size can be reduced up to 70% [23].

Chapter 4

Color Space

A color space is a model for representing color in terms of intensity values. There are many different color spaces such as RGB, HSV, HSL, Grayscale and CMYK, but in this thesis the focus lies on the first two. A color space is typically defined by a one to four-dimensional space where any point within this space represents a color. Sometimes an alpha-channel is used, this is a mask that indicates how transparent or how well the color merges when the color overlays another color.

4.0.1 RGB color space

The three dimensional RGB color space is composed of the primary colors red, green and blue, where each primary color represents a dimension. To create a desired color in this space the red, green and blue values are added together. Value for each channel vary from 0 to 1. Where (0,0,0) is black and (1,1,1) is white. This model is the most commonly used. The reason for this is because it's ideally suited for hardware implementations, and because the human eye strongly responds to red, green and blue. This is a color space often used in most (CRT) monitors and color raster graphics.

4.0.2 HSV color space

The three dimensional HSV color space stands for Hue, Saturation and Value, which are based on a painter's approach of coloring using Tint, Shade and Tone. This model can be represented by a cone shape. This model has a physiological basis as hue and saturation are related to the way human eyes perceive color [18]. Hue represents the color and is valued between 0 and 360. Saturation represents the richness of the color, the less saturation, the more bland and grey the color will be. Value represents the intensity of the color. This is

different from RGB where the combination of the dimensions incorporate the color intensity. The strength of this color space is that it's very intuitive: It's easy to describe a color in this space.

Chapter 5

The process

The goal of the application is to deliver create a similarity ranking for a target image. The process the application goes through to accomplish this is as follows:

1. Select the target image that you'd like to compare the entire image dataset with.
2. Select your desired color space and algorithm.
3. Create a color histogram for the selected image (see Data Extraction).
4. The application now iterates over all entries of the dataset. It creates a histogram for every image being iterated and calculate it's similarity to the target image. The results are then stored in an array.

The result of this process is a ranking of all images in similarity. Later we will use this data to compare the different color spaces and algorithms for the MIRFLICKR and Corel image dataset.

5.1 Data Extraction using color histograms

Extracting the color information from images is fairly straight forward. First the entire set of images is scaled so all images are roughly of equal size while respecting their width/height ratio. This is done to reduce computation time without removing any relevant data as a scaled imaged still represents the same content. An image's color histogram is constructed by counting the number of pixels for each color in the image. It would also be possible to use partial information from the image, this would require more advanced techniques of data extraction [4] [13] The data extraction is either done in RGB or HSV color space. This technique of representing color data is a very simple and low level technique that has been shown to have good results for

image indexing and retrieval tasks [21]. An image histogram refers to the probability mass function of the image intensities. This is extended for color images to capture the joint probabilities of the intensities of the three color channels. More formally, the color histogram is defined by:

the tuple $h(A,B,C)$ represent the dimensions of the 3 dimensional color spaces, either R,G,B or H,S,V. N is the size or number of pixels of the image.

This methods does have its flaws. Spatial information of the colors is ignored. rams for these images in figure

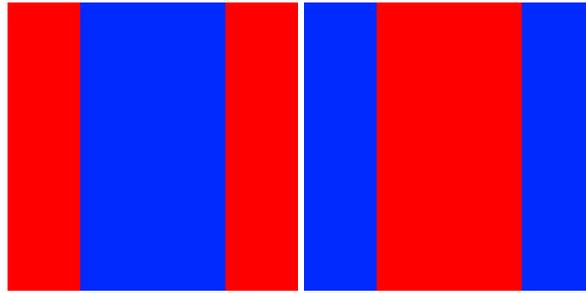


Figure 5.1: Results in identical color histograms

5.1 are more or less identical and are therefore considered to be the same image, which is wrong. A different but similar problems illustrated in figure 5.2 happens when an image is color shifted (increasing darkness or intensity of a certain color).



Figure 5.2: Results in identical color histograms

While the actual image may stay very similar, the resulting histograms may vary drastically. Certain algorithms such as the quadratic form distance try to solve this problem by taking into account the similarity of colors.

5.2 Distance calculation algorithms

There are many different algorithms for measuring similarity between color histograms. This is because visual perception determines image similarity opposed to probability distributions. Below are several algorithms which were implemented in the program. The first two are rather simple in it's calculations and are very lightweight compared to the latter two.

5.2.1 the Euclidean Distance

$$d^2(h, g) = \sum_A \sum_B \sum_C (h(A, B, C) - g(A, B, C))^2$$

Most commonly used is the Euclidean distance and variants of it. [5]. This method is very fast. It's complexity is $O(n)$. This method simply squares the difference of every color and sums them. The problem that this method has is that it only compares it's color with the exact same color of the other image. Take for example the following images: Although red and orange are intuitively much more alike that red and blue, the images are equally similar (or rather said, dissimilar) as this method does not take into account any similarity between colors. However, this is not necessarily a problem as there are many applications where this information is irrelevant [7]

All algorithms are in the form of $d(h, g)$ where h and g are color histograms and d calculates the distance between them.

5.2.2 Intersection Distance

This method was proposed by [26], showing that this method has good performance on partial matching of histogram. The lower part of the fraction is there to nullify any color in g that is not in h . Therefore only the colors that are in both h and g are used.

$$d(h, g) = 1 - \frac{\sum_i \min(h_i, g_i) e}{\sum_i h_i}$$

5.2.3 Quadratic Distance

$$d(h, g)^2 = (h - g)^t A (h - g)$$

$$\text{RGB: } a(i, j) = 1 - \frac{\text{Euclidean}(i, j)}{\text{Maxistance}}$$

$$\text{HSV: } a(i, j) = 1 - \frac{1}{\sqrt{5}} \left(\sqrt{(v_i - v_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2 + (s_i \sin h_i - s_j \sin h_j)^2} \right)$$

Euclidean(i, j) is the Euclidean distance of color i and j in RGB color space.

Maxistance is the the largest value of *Euclidean*(i, j), in RGB color space this would be the Euclidean distance between black and white.

This method uses a similarity matrix denoted by A . A is of size $h.size * h.size$ where every row and every column represents a color in the histogram h . An entry $a(i, j)$ of A represents the similarity of the i_{th} and j_{th} color of histogram h . There are different formulas for different color spaces, this is because of the shape of color spaces. RGB color space can be represented by a cube, making the formula rather simple. HSV color

space, however, is represented by a cone shape, resulting in the formula above.

The quadratic distance resolves the problem mentioned previously where similarity between colors was not taken into account. This solution is very computational heavy as every color is compared to every other color, resulting in a complexity of $O(n^2)$ where n is the number of colors [6].

5.2.4 Earth Mover's Distance

Earth Mover's Distance (EMD) calculates the minimum cost needed to transform one probability distribution into another one. This method was developed by Rubner et al. of Stanford University [15]. Because this algorithm is very slow, there have been many attempts on improving the algorithm in computation time [25] [20] [11]. The implementation of EMD that was used was the one by Pele O. et al [14].

$$d(h, g) = \left(\min_{\{F_{ij}\}} \sum_{i,j} F_{ij} D_{ij} \right) / \left(\sum_{i,j} F_{ij} \right) \text{ s.t } F_{ij} \geq 0$$

$$\sum_i F_{ij} \geq h_i$$

$$\sum_j F_{ij} \geq g_j$$

$$\sum_{i,j} F_{ij} \min(\sum_i h_i, \sum_j g_j)$$

where $\{F_{ij}\}$ denotes the flow. Each F_{ij} is the amount of data transported between i and j . D_{ij} denotes the distance between i and j .

Chapter 6

Image Dataset & Classification

6.1 Types of classification

Image classification is an attempt to label (textually) an image with identifiers. Identifiers are usually determined by the content of the image, although an identifier could be anything the annotator wants it to be. There are two main ways to image classification: supervised and unsupervised image classification. In this thesis only supervised image classification is used.

6.1.1 Supervised image classification

Supervised image classification uses training sets to create a descriptor for each predefined class by the annotator. The images of the training sets are selected in manner such that every class has images that are very representative for that specific class. The descriptors contain certain common information that the training set's images contain. The classifier can then use these descriptors to determine to what class an image from the test set belongs to.

Unsupervised image classification

Unsupervised image classification does not use a training set. It uses a clustering technique which measure the distance between images and then groups the images based on their common features. Each group then represents a classification label.

6.2 Image Datasets

In this section we experiment on two different datasets. MIRFLICKR and Corel. We chose these because of their difference in structure, but also because both have been reported as being the most popular scientific image retrieval datasets [22].

6.2.1 MIRFLICKR25k Image Dataset



Figure 6.1: Random images from the MIRFLICKR dataset.

This dataset has been widely used for image classification [3] [17] [8]. All images in this dataset are created by users of the flickr.com website. The dataset consists of 25000 images, which are all tagged by said flickr users. We will only be looking at the 7 most common tags as there are over a 1000 different tags used in this dataset. The tags used are: beach, clouds, nature, night, sky, sunset and water.

The classification process

A form of supervised image classification was used. From the 25,000 images a training set and test were build. To build the training set 300 images were chosen per class to be representative for the specific class. The remaining images made up the test set. Using the training set, descriptors are build for every class by simply creating color histograms for each image in the class' training set, adding them together and normalising its results. This results in a color histogram that contains with peaks at colors that are most common through out the class' training set. We now run the process described in chapter 5 with a descriptor as the target image. This process is repeated for every descriptor. After this the classifier classifies every image by the class that has the highest similarity with the image.

Performance & Results

The descriptors, made by the methods above, hold no meaning full information regarding the tag it's related to. Classification using this system seems meaningless. Every image is either classified incorrectly, or correctly for the wrong reasons. This is caused by the following:

1. The meaning of a certain tag varies depending on the user.
2. The correlation between a tag and an image's color scheme is very weak.

Improvements could possibly be made in the classification process by including more information that just color histograms (see chapter 3). The results from the MIRFLICKR dataset are inconclusive at this point and is a direction for future research.

6.2.2 Corel Image Dataset



Figure 6.2: Random images from the Corel dataset.

This is a dataset that has been specifically made for comparing algorithms and has been used for many different experiments [27] [10] [2] [16]. This dataset has 10 categories, africans, beach, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and food. Each category is build from a 100 images, which are all from the same image set. For example: the category dinosaurs contains images which are all drawn in the same style by the same artist. Opposed to the MIRFLICKR dataset, these categories do have a strong correlation between the category and the image's color pallet.

The classification process

Supervised image classification was used again. For each category 10 images were selected to represent the category in the training set. We then build the descriptors for the categories. The rest of the process is

identical to the classification process used for the MIRFLICKR dataset.

Performance

For each category we sum the results from the classification process of the images that belong to that category. We are then able to calculate the performance per category by means of precision and recall.

$$\text{Precision} = \frac{A}{A+B}$$

$$\text{Recall} = \frac{A}{A+C}$$

A is the number of relevant images that are retrieved, B is the number of irrelevant images that were retrieved and C is the number of relevant images that were not retrieved.

6.2.3 Results

The figures 6.3 through 6.12 present the precision and recall graphs for each category. A legend can be found in the top right corner of each figure. Each colored line represents a different combination of color space and algorithm. On the Y-axis we have the precision and recall is on the X-axis. Only 10% of the test set images is relevant for each category, therefore we are most interested in the performance of the algorithms at the 0.1 point of recall. From these graphs we are able to observe the following:

- We see that EMD seems to give decent results when using HSV color space, while RGB color space gives almost always a bad result.
- The Euclidean distance gives very good results regardless of color space used, however using HSV gives better results. From this we can conclude that the cross-bin information used by EMD and QCD is nearly irrelevant.
- No algorithm gives good results for the category "Beach". The images in the beach category vary heavily in color scheme. This results in the same problem we had with the MIRFLICKR database where the image descriptors held no relevant information.
- In the category "Dinosaurs" every algorithm, except for EMD using HSV color space, gives a very good result. The background of each image in this category is a paper sheet, and all images are of dinosaurs which skin only varies in a small number of colors. Why EMD using HSV color space gives bad results is unclear.
- For the category "Buildings", the Euclidean distance in both color spaces gives the best results by a long shot. We cannot say why this is with certainty. All images in this category are of old monumental

buildings. Most of them are from the same period in history, resulting in similar techniques of building. Therefore the color range of each building is very similar; Resulting in high peaks in the color histograms for that specific color range. The Euclidean distance picks up this trend and pretty much ignores the rest of the color histogram. The other algorithms try to find meaning from the entire color histogram, therefore giving worse results.

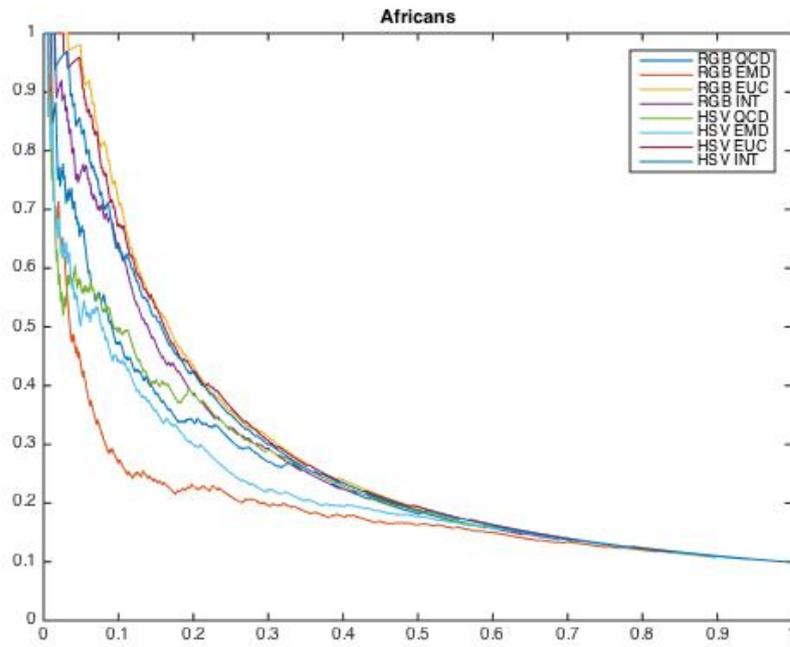


Figure 6.3: Accuracy in category "africans".

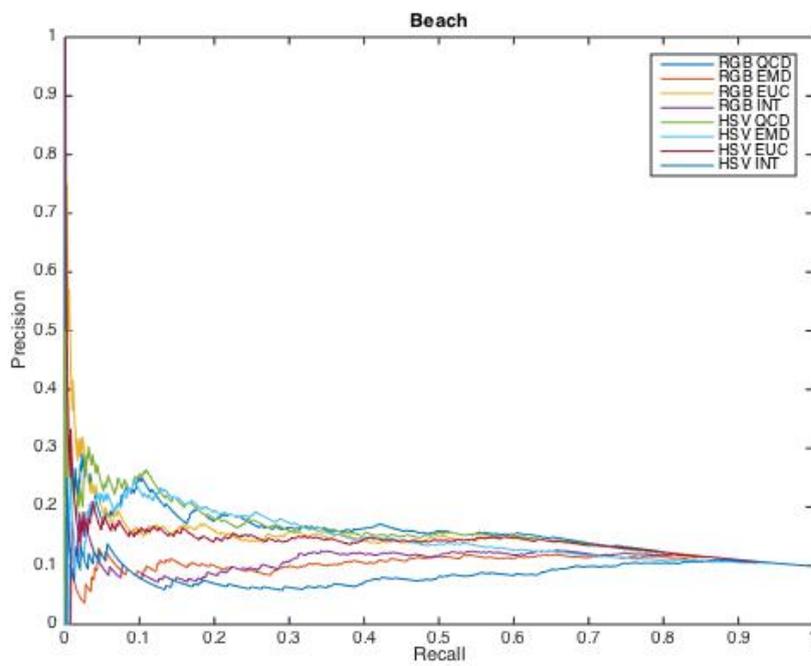


Figure 6.4: Accuracy in category "beach".

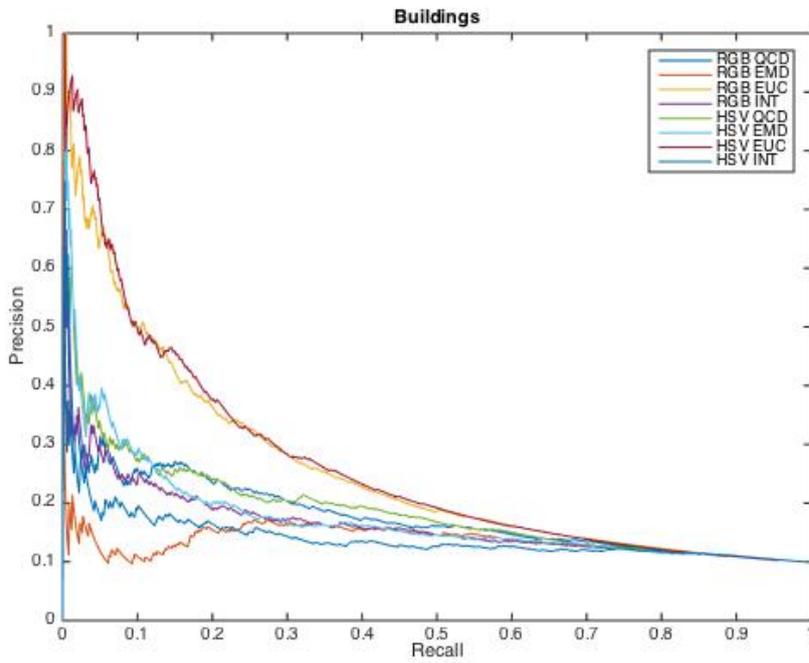


Figure 6.5: Accuracy in category "buildings".

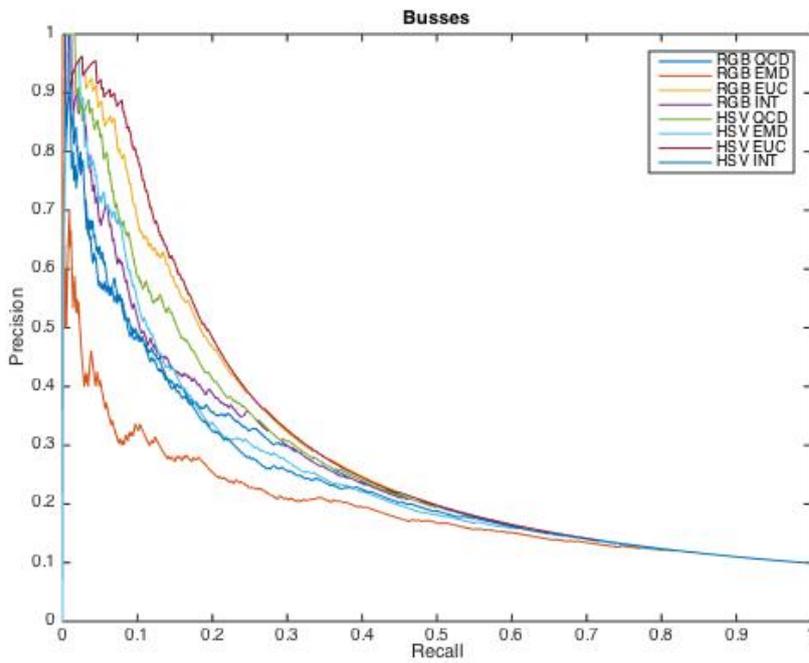


Figure 6.6: Accuracy in category "busses".

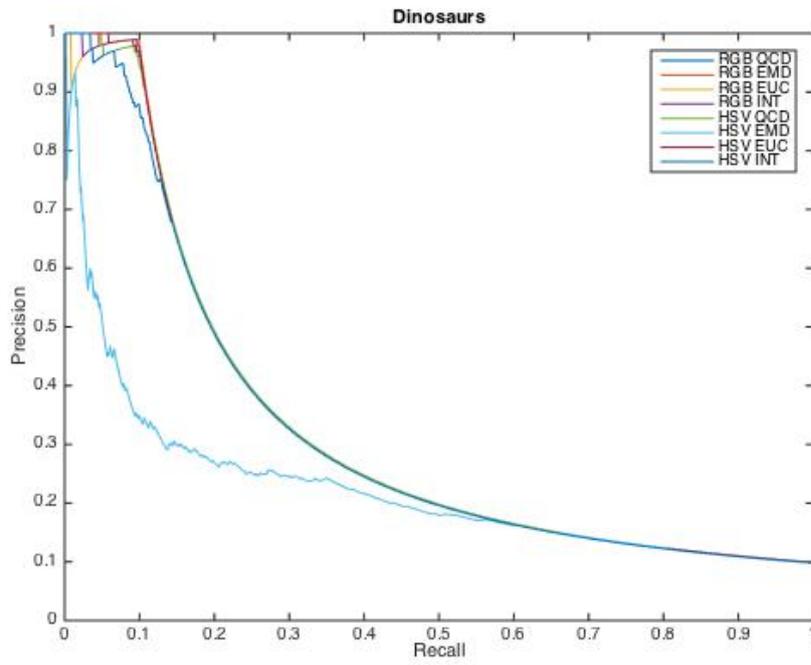


Figure 6.7: Accuracy in category "dinosaurs".

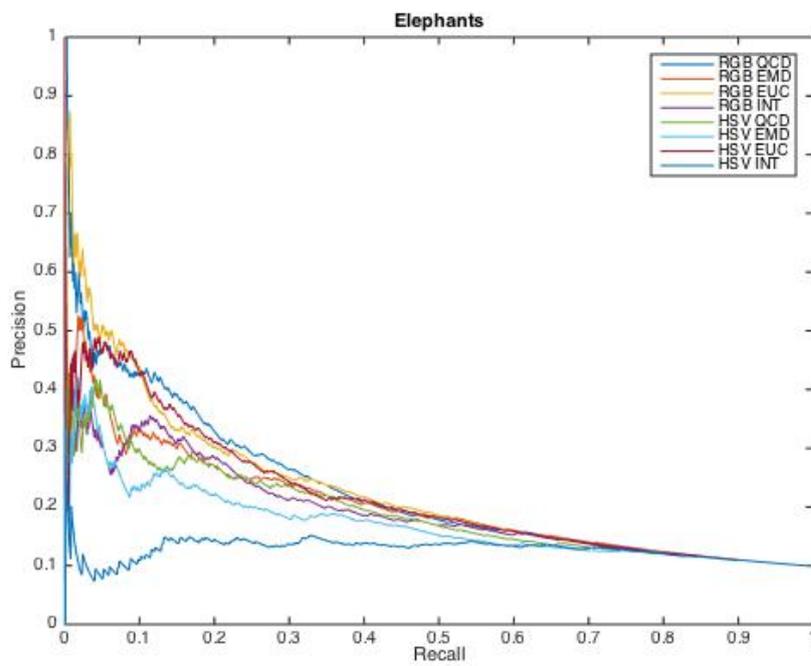


Figure 6.8: Accuracy in category "elephants".

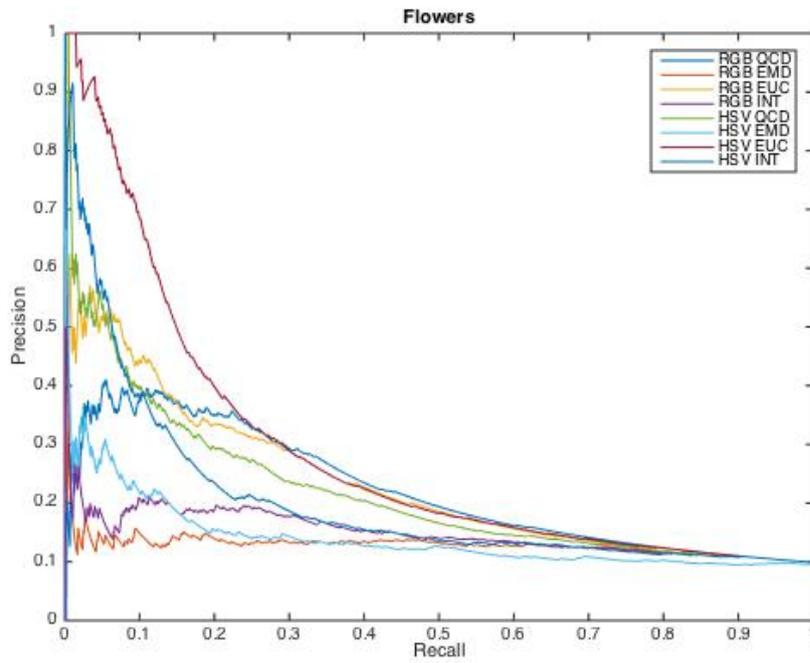


Figure 6.9: Accuracy in category "flowers".

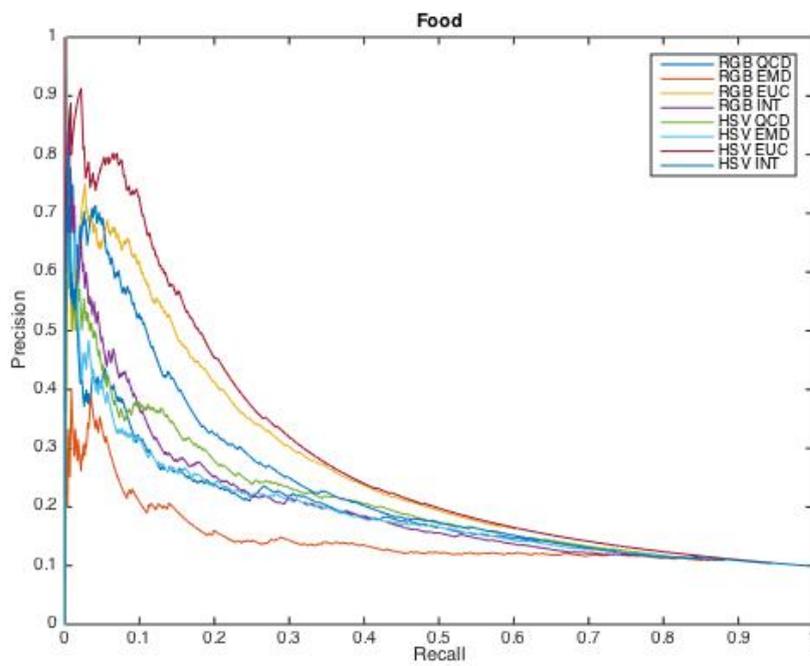


Figure 6.10: Accuracy in category "food".

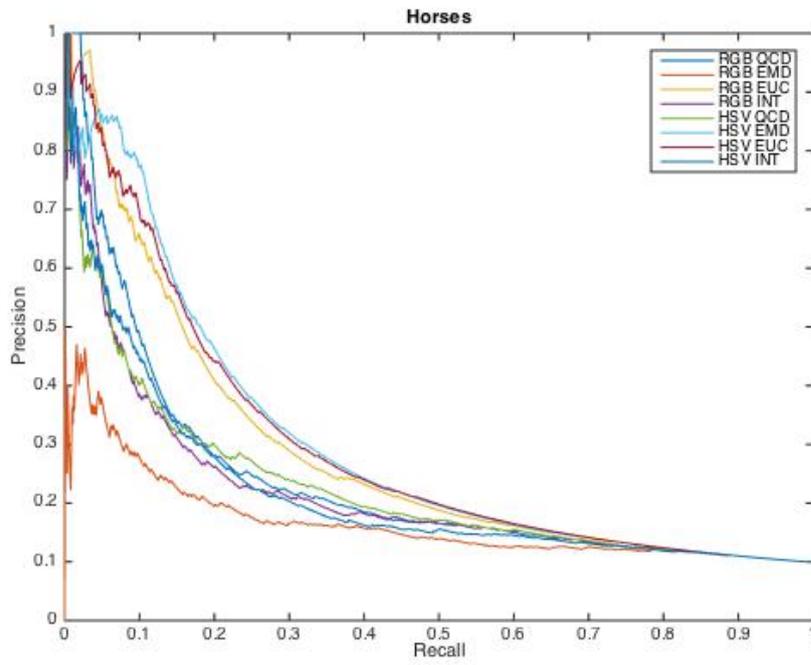


Figure 6.11: Accuracy in category "horses".

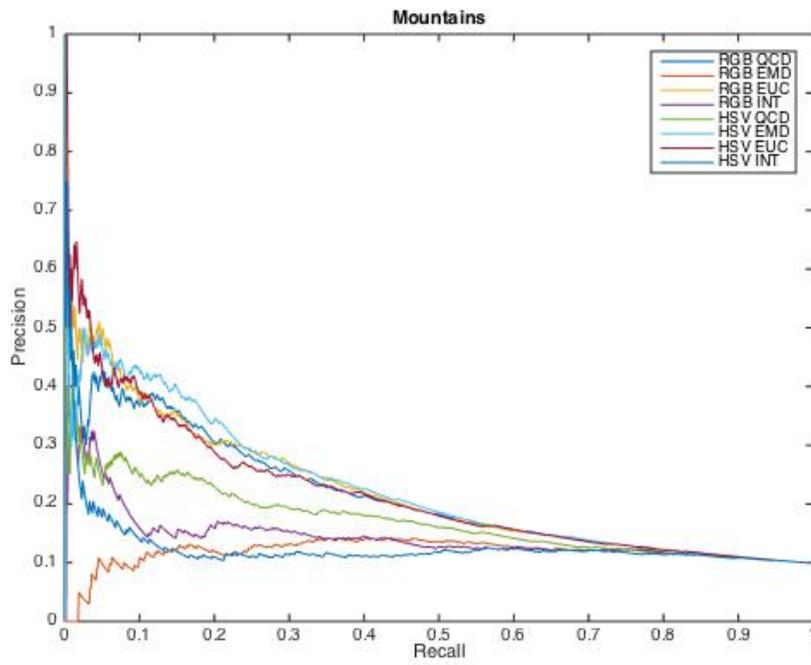


Figure 6.12: Accuracy in category "mountains".

Chapter 7

Conclusions

7.1 The differences in the two datasets

By running the classification process on two different image datasets, we are able to see the limits of this process. Because the MIRFLICKR dataset's categories are not strongly related by a color scheme, this process is unable to extract any relevant information from the images. Resulting in very bad descriptors to represent each category. The Corel image dataset does have this strong correlation in color scheme and category. Therefore the process does give meaning full results.

7.2 Final Conclusion

HSV seems to be the best color space to use. In almost all cases it seemed to give better results than RGB. Of all the algorithms the Euclidean distance gives the best results. However these conclusions are only true for this specific setup. Including more information than just color histograms, or using a different dataset might result in a very different outcome. Classification using only color histograms seems to be only possible when there is a strong correlation between the categories and a certain color scheme.

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