EEE3032 - Computer Vision and Pattern Recognition Coursework Assignment

# VISUAL SEARCH OF AN IMAGE COLLECTION

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# Abstract

The aim of this report is to provide an in-depth analysis of the techniques implemented to develop and test a fully-functional visual search tool.The tool uses different image descriptors and distance measures to rank the images in a database according to their similarity to several key images selected by the user. It also performs a statistical analysis on the efficiency of the techniques implemented.

# Table of Contents

# 1 Introduction

Nowadays, a common way to identify and classify similar images within large image sets is to implement what are known in the computer vision field as visual searching techniques. The image classification process is based on computing an accurate image descriptor for a query image manually selected by the user or automatically selected by the system, which will then be represented in an N-dimensional feature space. The rest of the images in the database are then represented in the same feature space. The distance from each image representation as a point in the feature space to the query image point in the same feature space determines how similar the images are in terms of the measured content.

The computer vision techniques applied to compute the image descriptors in this project include the use of global colour histograms, spatial colour grids, edge orientation histograms, colour moment descriptors, Principal Component Analysis (PCA), and a new and innovative technique, as well as a combination of some of these techniques into a single image descriptor to increase accuracy. Additionally, the results obtained using different distance measurements such as Euclidean, L1 norm, L3 norm, Bray Curtis, Canberra and Mahalanobis distances were compared. The techniques' efficiency was tested by computing Precision Recall (PR) statistics with their corresponding Average Precision (AP) and Mean Average Precision (MAP) values.

# 2 Visual Search Techniques

## 2.1 Global Colour Histogram

A global colour histogram is commonly used in image processing as a descriptor that represents the overall colour distribution of an image. For a digital Red, Green and Blue (RGB) image, each column of the histogram corresponds to the number of pixels of the image of a particular colour.

In order to compute the global colour histogram of an image, each pixel of the image is represented as a point in the three-dimensional (3D) feature space determined by the dimensions Red (R), Green (G) and Blue (B). A factor Q equal to an integer represents the quantisation level, with every colour pixel being converted to Q divisions by using r'=floor(r*Q/256) for the red colour, g'=floor(g*Q/256) for the green colour and b'=floor(b*Q/256) for the blue colour. The formula bin=r'(Q2̂) + g'(Q1̂) + b' can be used to determine which histogram bin each pixel corresponds to [2]. To illustrate this, given that for a specific image Q was chosen to be equal to 4 (Q=4), then the new pixel values r',g' and b' will have a range [0,3], resulting in a 64 bin histogram.

For the global colour histogram technique, once the query image has been represented in the feature space by following the above-mentioned process, a distance measure such as the Euclidean or the L1 norm distance is used to classify or rank the rest of images in the database according to their proximity to the query image in the feature space. The histograms however, do not contain any spatial information about the distribution of the different colour pixels throughout the image and are therefore limited in their ability to identify similar images [4].

## 2.2 Colour Grid

The spatial grid technique for visual searching consists of computing a descriptor that takes into account not only the colour but also its spatial distribution within an image.

The colour grid descriptor of an image can be computed by dividing the image into equal divisions i.e into a grid, and calculating the average RGB value for each of the divisions or grid cells. The image descriptor can then be computed by concatenating the average RGB colour values for all the cells in the image, and represented as a single point in the feature space [2]. The images from the database that most accurately resemble the query image can be found by applying a distance measure such as the Euclidean or the L1 norm distance to identify and rank the images closest to the query image in the feature space.

### 2.3 Edge Orientation Histogram (EOH)

To compute the edge erientation histogram of an image, the RGB image pixels are first converted to greyscale values by using the formula Y = 0.30*R + 0.59*G + 0.11*B for each pixel, where Y is the greyscale pixel value, R is the red pixel value, G is the green pixel value and B is the blue pixel value. The image descriptor is computed by applying the vertical and horizontal Sobel filters to detect the edges in the image, after which the image is divided into equal grids or cells. The magnitude and angle values of all the edges in each of the cells are then calculated, with the angle values being converted to the range 0 to 2pi and the edge magnitude being thesholded in order to select only the strongest edges in each cell, hence reducing the computational expense of the algorithm [2]. For a specific level of angular quantisation Q, which is usually equal to eight levels, the histogram of the selected edges is computed. The image descriptor will consist of concatenating the histograms for each cell in the image into a long vector that can be represented in the feature space.

Contrary to the global colour histogram and the colour grid techniques, the edge orientation histogram descriptor is based on texture rather than colour values, making it a useful technique to detect specific shapes and objects.

### 2.4 Colour Grid and Edge Orientation Histogram Combined

The colour grid and the edge orientation histogram can be combined to create an image descriptor that takes into account both spatial colour distribution and edges. This descriptor is computed by concatenating the colour grid RGB vector values with the edge orientation histogram values into a long vector which constitutes the image descriptor. This descriptor can then be represented in the feature space.

### 2.5 Principal Component Analysis (PCA)

The descriptors implemented in visual searching techniques must be as discriminative as possible for increased efficiency. In addition, the descriptors must be compact i.e they must have account for as few dimensions of the features as possible while still taking into account the variation of the data. This will allow the user to store large image collections while avoiding the completion of unnecessary calculations.

Principal Component Analysis (PCA) is a technique that can be used to easily visualise the variations of data which is initially represented in a high-dimensional space in a lower dimensional space. [5] It is useful for situations where the data presents significant variability in less dimensions than there are directions in the space. As an example, an A4 sheet of paper exists in a three-dimensional space. However, most of its variation is in the dimensions that correspond to its height and width, with the sheet's variation in the direction corresponding to its depth being almost negligible. Therefore, the sheet of paper has two degrees of freedom, and its null space is the one corresponding to the sheet's depth dimension. If an eigenmodel of the paper sheet is computed, the eigenvalue corresponding to the dimension in which the sheet expresses a negligible variation will be almost zero and can therefore be eliminated from all further calculations.

To implement PCA, the data mean is substracted from all the points, after which the covariance matrix as well as its corresponding eigenvalues and eigenvectors are calculated. Once this calculation has been completed, the null space, if existent, can be observed through the eigenvalues. The eigenvectors corresponding to the null or significantly low eigenvalues are then eliminated from further calculations to allow for faster processing. The process of casting the data to a lower dimensional space can be completed by eliminating the null space eigenvectors from the eigenvector matrix, and multiplying the data by the inverse of this new shrunk matrix [2].

## 2.6 Additional Image Descriptors

### 2.6.1 Colour Moment Descriptor

An additional image descriptor based on colour moments of points was implemented for this project. This technique is affine invariant and is usually implemented for both colour and shape description. It was incorporated into the project and evaluated using various queries and distance measures.

To compute this image descriptor the mean, variance, and skew values for the red, green and blue components of each pixel in the image were computed. These values were then concatenated into a long vector, which is the image descriptor represented in the feature space [7].

## 2.7 Color Moment Descriptor and Global Colour Histogram

The colour moment descriptor was combined with the global colour histogram to analyse whether combining both the global colour of the image and the spatial information of the colour produced better retrieval statistics than the individual colour descriptors. For this, the global colour of the image is concatenated with the colour moments of the image into an array constituting the feature file for the image.

### 2.7.1 New Image Descriptor

A new experimental image descriptor was incorporated into the project and evaluated against the standard image description tools. The descriptor is a variation from the colour grid image descriptor and its implementation purpose was to determine whether analysing every pixel in the individual cells is necessary or whether several 'key' pixels could be analysed instead, allowing for a faster algorithm with less memory requirements.

For this technique, the image is first divided into equal grids or cells. For each cell, the RGB values are extracted at nine positions: top left, top middle, top right, middle left, middle middle, middle bottom, bottom left, bottom middle, and bottom right. The number of positions extracted can vary from four to all the positions i.e standard colour grid, depending on the processing power and accuracy needed. The motivation behind this is that computation power can be saved for operations that do not require excessive accuracy.

## 2.8 Distance Measures

### 2.8.1 Main Distance Measures

Two main distance measures were used throughout this project: the Euclidean or L2 norm distance and the Mahalanobis distance. If A and B are the two points in an n-dimensional space, the Euclidean distance is given by $d = \sqrt{\sum_{i=1}^{n} (B_i - A_i)^2}$. The Mahalanobis distance differs from the Euclidean distance in that it measures the distance in units of standard deviation, therefore taking into account not only the mean of the data but also its spread. The Mahalanobis distance is given by $d = \sqrt{\sum_{i=1}^{n} \frac{(B_i - A_i)^2}{Vi}}$ where V represents the eigenvalues of the space [2].

### 2.8.2 Additional Distance Measures

Even though the Euclidean and the Mahalanobis distance measures are the most commonly used, there are other distance measures that can be applied to visual search processes. These include the complete set of L norm measures, the Bray Curtis distance measure, which views the space as a grid similar to the L1 norm or Manhattan distance, and the Canberra distance, which is a weighted version of the Manhattan distance measure.

To compute these between two points A and B in an n-dimensional space, the set of L norm distance measures is given by $L_\alpha = (\sum_{i=1}^{n} \mid B_i - A_i \mid^\alpha)^{\frac{1}{\alpha}}$, the Bray-Curtis distance is given by $d = \sum_{i=1}^{n} \frac{|B_i - A_i|}{(B_i - A_i)}$ and the Canberra distance is given by $d = \frac{\sum_{i=1}^{n} |B_i - A_i|}{\sum_{i=1}^{n} |B_i - A_i|}$.

### 2.9 Evaluation methodology

One of the most commonly used methods to measure the efficiency of a visual search system is to compute the Precision-Recall (PR) statistics and curve. For a given system, the precision value is given by the number of returned results that are relevant to the query, and the recall value is given by the number of relevant results that have been returned. The PR curve is the plot of the precision values for all the images considered in the vertical axis against the recall values for all the images considered in the horizontal axis. A greater area under the curve indicates a better performance of the system.

The Average Precision (AP) for the system against each query can be computed by calculating $AP = \frac{\sum_{n=1}^{M} P(n) * rel(n)}{T}$ where P(n) is the precision of the top n results, rel(n) will equal 1 is that particular result is relevant and 0 if not, and T is the total number of relevant images in the set[2]. Averaging the AP values for the different queries over all queries gives the value for the Mean Average Precision (MAP) of the system, concordant with the area under the PR curve.

Additionally, a technique that can be used for the evaluation of texture-based supervised classification systems consists of computing a confusion matrix to evaluate the classifiers' performance. The confusion matrix is a square matrix that compares the ground truth for the data, which is annotated by an expert prior to performing the search, to the image classifier results. Each element in the matrix is normalised to provide a fair representation of the number of items correctly identified in each category. The value obtained from averaging the confusion matrix's diagonal is the Mean Average Precision (MAP) and represents the overall accuracy of the algorithm used. The Receiver Operator Curve (ROC) can be computed using this data to provide an in-depth analysis of the system's performance. Nevertheless, it has been shown that for skewed datasets the PR curve provides a more accurate analysis of the algorithm's performance [3].

# 3 Use of the Tool

The project content includes seven files to compute the image descriptors following the different techniques: global colour histogram, colour grid, edge orientation histogram, colour grid with edge orientation histogram, colour moment descriptor, global colour histogram with colour moment descriptor, and the new technique. It contains six files to compute different distance measures: Euclidean, Mahalanobis, L1 norm, L3 norm, Bray Curtis and Canberra distance. Moreover, the files 'Hist_Array.m' and 'Confusion_Matrix.m' were implemented in order to compute histograms [8] and confusion matrices respectively. Additionally, the project incorporates seven visual search files: 'Visual_Search_GCH.m' for the global colour histogram, 'Visual_Search_CG.m' for the colour grid, 'Visual_Search_EOH.m' for the edge orientation histogram, 'Visual_Search_CG_EOH.m' for the colour grid combined with the EOH, 'Visual_Search_M.m' for the colour moment descriptor, 'Visual_Search_GCH_M.m' for the global colour histogram with colour moment descriptor, and 'Visual_Search_NEW.m' for the new technique.

The project includes seven test files to ensure the correct functioning of each technique: 'Test_GCH.m' for the global colour histogram, 'Test_CG.m' for the colour grid, 'Test_EOH.m' for the edge orientation histogram, 'Test_CG_EOH.m' for the colour grid combined with the edge orientation histogram, 'Test_M.m' for the colour moment descriptor, 'Test_GCH_M.m' for the global colour histogram with colour moment, and 'Test_NEW.m' for the new technique. The results of the tests can be found in subsequent section 4 of this document.

The different visual searches are performed by running » [outdisplay r p ap] = "Visual Search File Name"(queryName, dist, PCA) where the queryName is the name of the query, dist is the distance measure and PCA is a boolean equal to true if PCA has to be performed on the data. The distance is determined by 'E' for Euclidean, 'L1' for L1 norm, 'L3' for L3 norm, 'B' for Bray Curtis and 'C' for Canberra distance. The function returns the top 10 results (outdisplay), an array containing the recall values for all the images in the database (r), an array containing the precision values for all the images in the database (p), and the Average Precision value (ap) for the input query. The Visual Search File Name can be VS_CG for the colour grid, VS_EOH for the edge orientation histogram, VS_CG_EOH for the colour grid combined with the edge orientation histogram, VS_M for the colour moment, VS_GCH_M for the global colour histogram combined with colour moments and VS_NEW for the new technique.

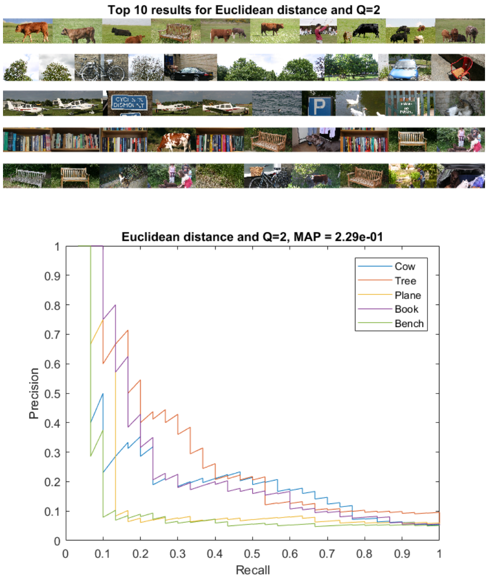
Each test file outputs two figures. The first figure contains, for five different query images, the top 10 similar images from the database. The second figure includes the PR-curves for all the queries and the Mean Average precision (MAP) of the system calculated from the Average Precision (AP) for each query.

The program is run by executing the appropriate descriptor file followed by the visual search file. Initially, the descriptor files were called by the visual search files in order to simplify the running process for the user. However, due to the high computational expense this approach caused, the descriptor and visual files were implemented as separate modules called by the test files. Nevertheless, the system's modularity allows for this to be modified easily if needed.

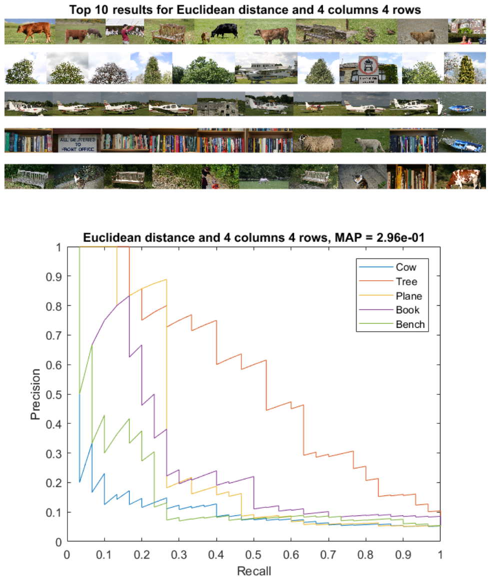
# 4 Experimental Results and Testing

The visual search system was evaluated in the above-mentioned test files by ranking the 591 images from the Microsoft Research (MSVC-v2) dataset, which belong to 20 different classes, according to their similarity to five queries selected from the database, each of which belong to a different class: cow, tree, plane, book and bench. Different distance measures, quantisation levels, grid sizes, and PCA results were compared. For the colour descriptors, the Precision-Recall (PR) statistic curve for the 591 images was calculated and plotted, and the Average Precision (AP) values were calculated for each query together with the system's overall Mean Average Precision (MAP) value. A function to calculate the confusion matrix was computed and is available. however, the PR curves and MAP values were chosen over the confusion matrix as the method to evaluate the system. This is due to the reasons explained in section 2.8 of this document and the possibility of the top 10 results images output by the classifier to contain both relevant and irrelevant images to the four queries, which, in turn, reduces the efficiency of the matrix as an evaluation metric.

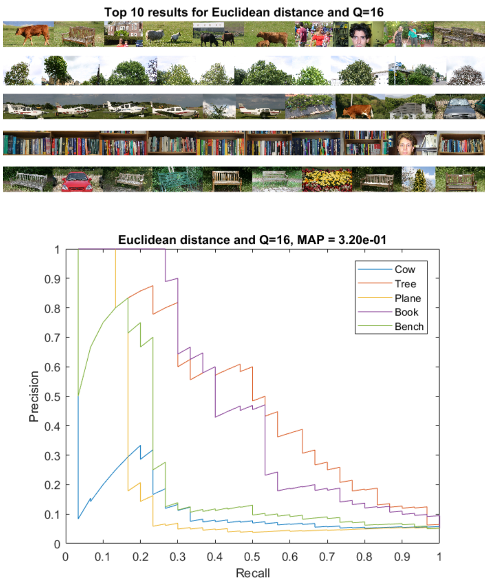
The results for the global colour histogram, colour grid and edge orientation histogram descriptors using the five different distance measures were compared. For the image descriptors that combine several techniques, such as the colour grid combined with the edge orientation histogram and the colour moments with the global colour histogram, and for the new technique, the tests were performed using the parameters that showed higher acccuracy for the individual techniques and compared using Euclidean distance. PCA was then performed on the global colour histogram, the edge orientation histogram, and the colour moment techniques to project the data into a lower dimensional space. Due to the data being projected without any loss of information, using the Euclidean distance would provide the same results as the Non-PCA Euclidean distance results. Therefore, the Mahalanobis distance metric was used to perform the main analysis of the visual search techniques' performance [6]. The results for PCA with Euclidean distance as well as some extra tests performed on the data can be found in the Appendix A.



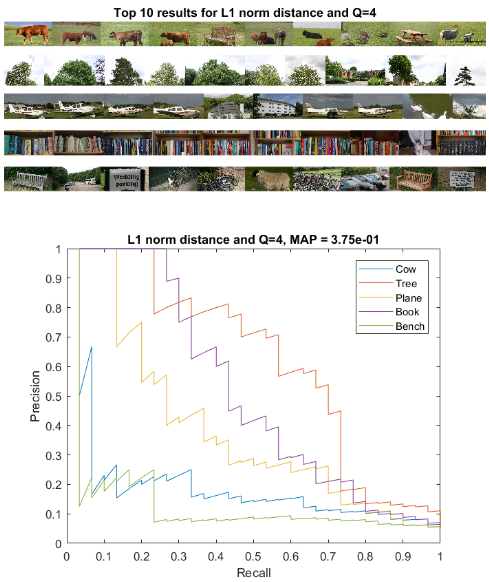

1. Global Colour Histogram results for Euclidean distance and Q=2



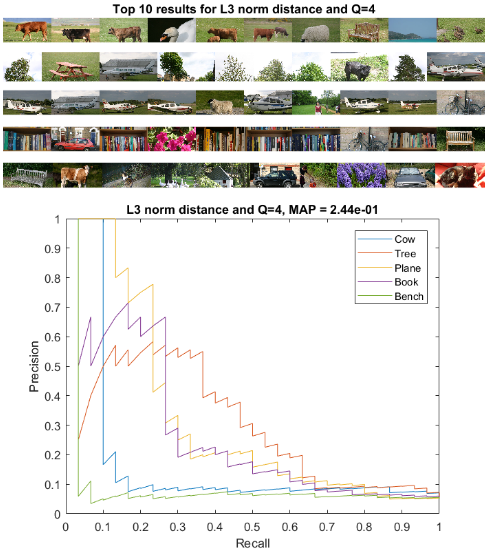

2. Global Colour Histogram results for Euclidean distance and Q=4



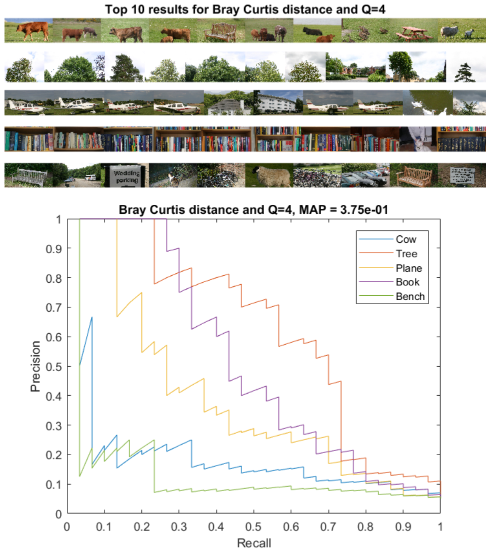

3. Global Colour Histogram results for Euclidean distance and Q=16



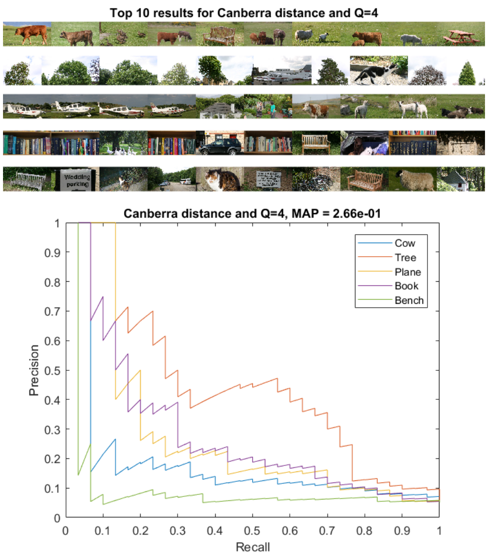

4. Global Colour Histogram results for L1 norm distance and Q=4



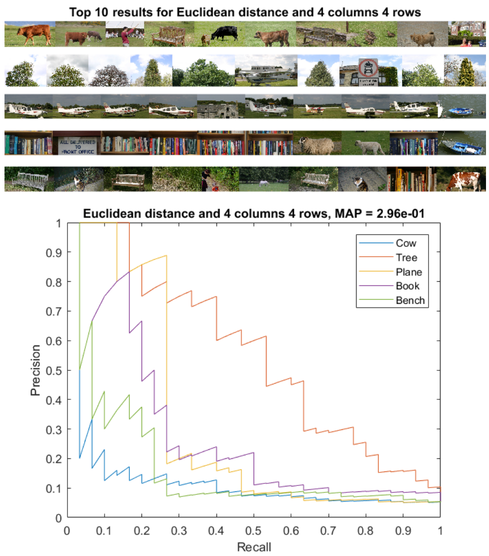

5. Global Colour Histogram results for L3 norm distance and Q=4



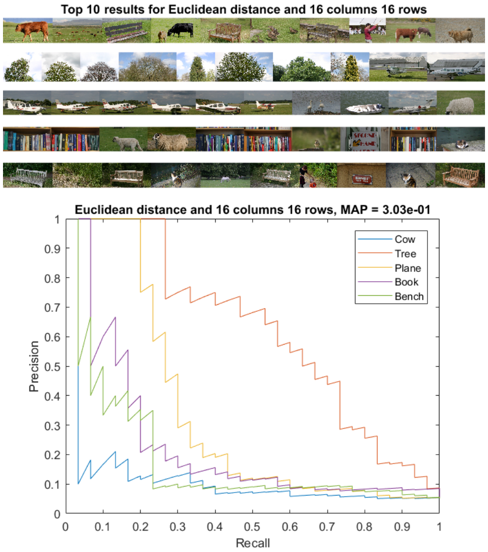

6. Global Colour Histogram results for Bray Curtis distance and Q=4



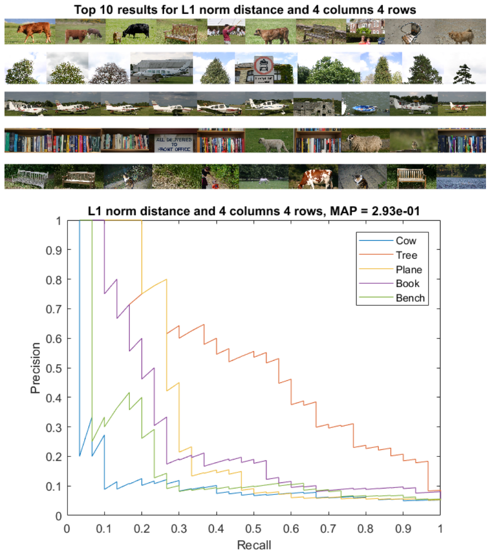

7. Global Colour Histogram results for Canberra distance and Q=4



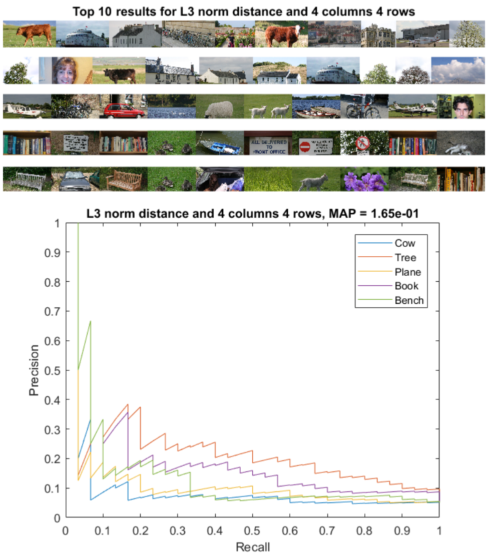

8. Colour Grid results for Euclidean distance and 4 columns 4 rows



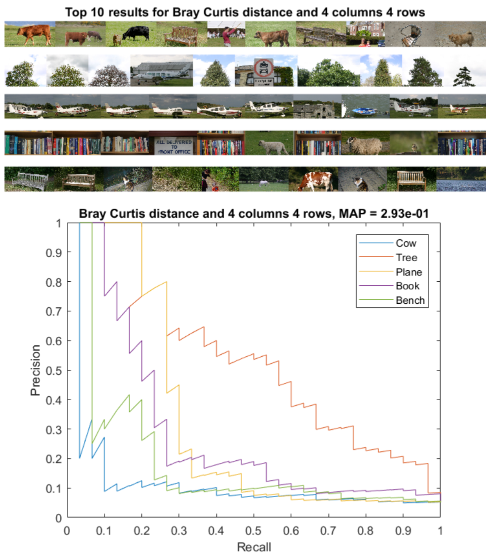

9. Colour Grid results for Euclidean distance and 16 columns 16 rows



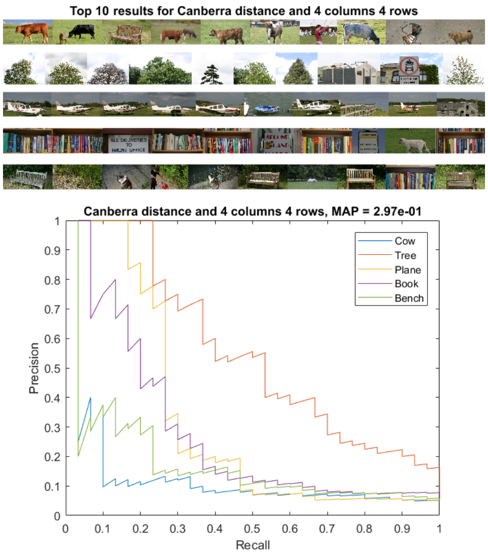

10. Colour Grid results for L1 norm distance and 4 columns 4 rows



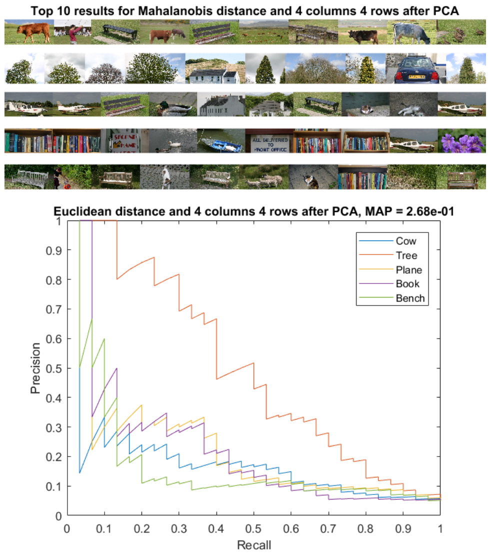

11. Colour Grid results for L3 norm distance and 4 columns 4 rows



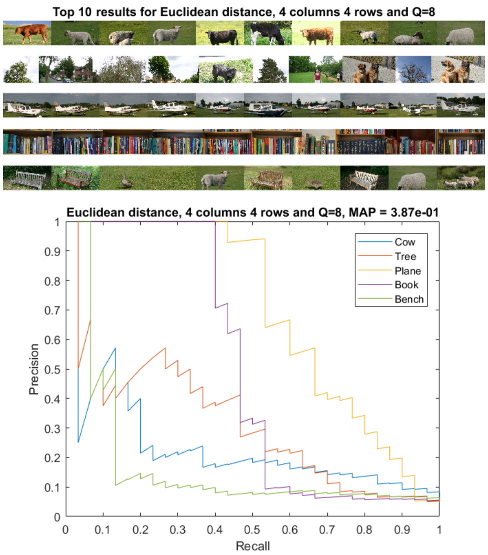

12. Colour Grid results for Bray Curtis distance and 4 columns 4 rows



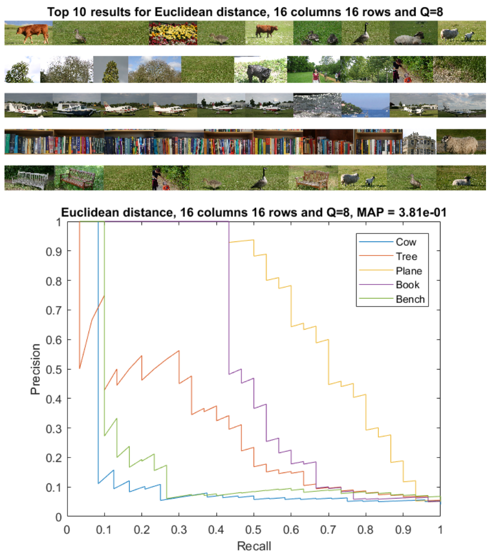

13. Colour Grid results for Canberra distance and 4 columns 4 rows



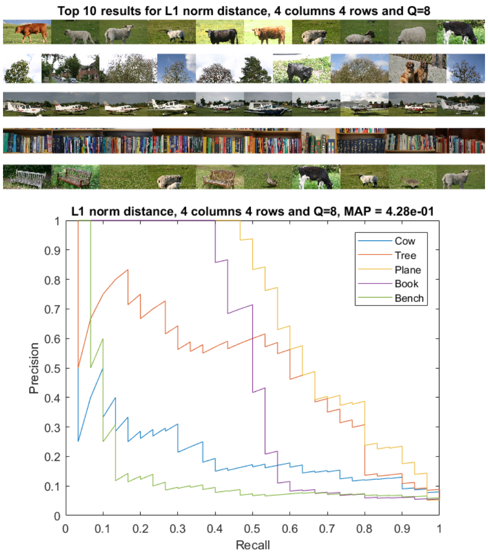

14. Colour Grid results for Mahalanobis distance and 4 columns 4 rows after PCA



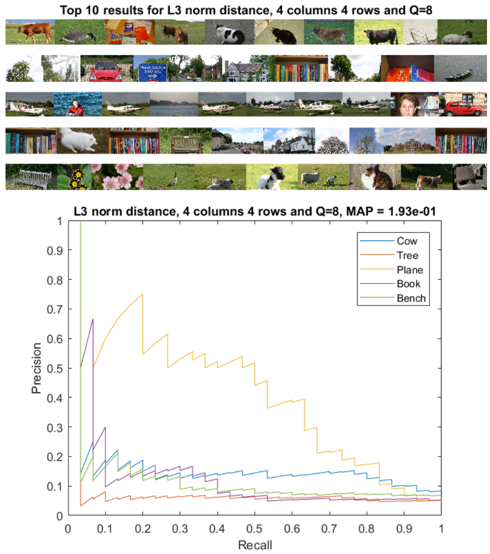

15. Edge Orientation Histogram results for Euclidean distance, 4 columns 4 rows and Q=8



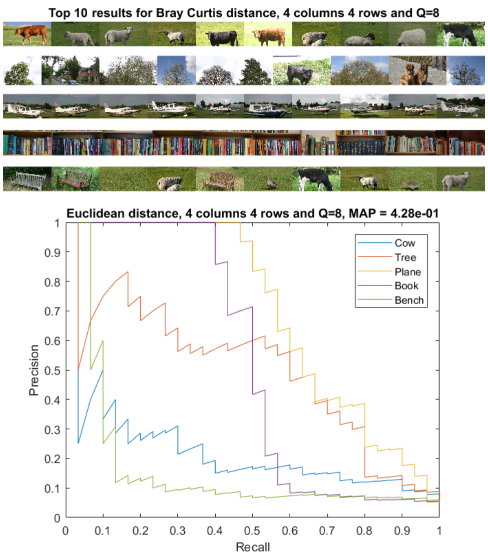

16. Edge Orientation Histogram results for Euclidean distance, 16 columns 16 rows and Q=8



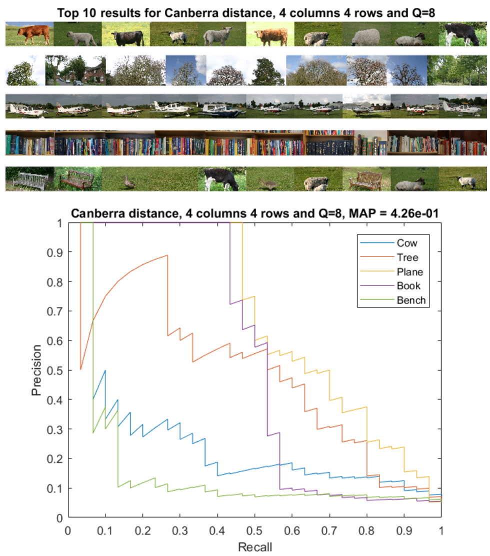

17. Edge Orientation Histogram results for L1 norm distance, 4 columns 4 rows and Q=8



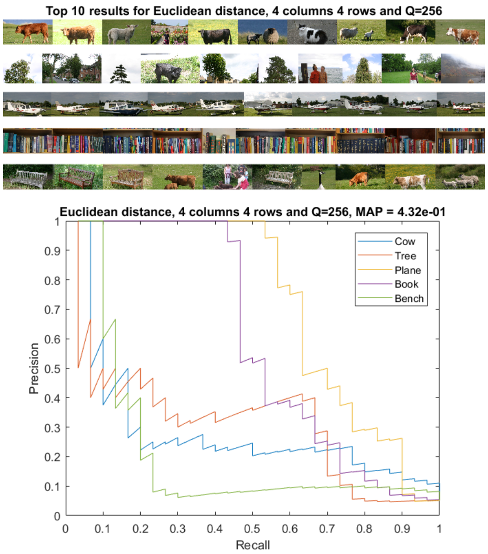

18. Edge Orientation Histogram results for L3 norm distance, 4 columns 4 rows and Q=8



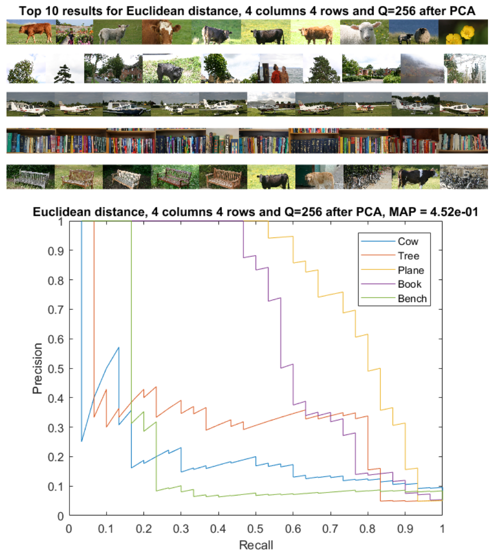

19. Edge Orientation Histogram results for Bray Curtis distance, 4 columns 4 rows and Q=8



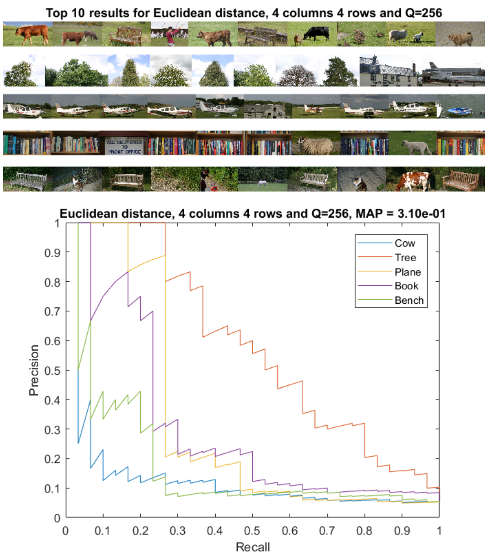

20. Edge Orientation Histogram results for Canberra distance, 4 columns 4 rows and Q=8



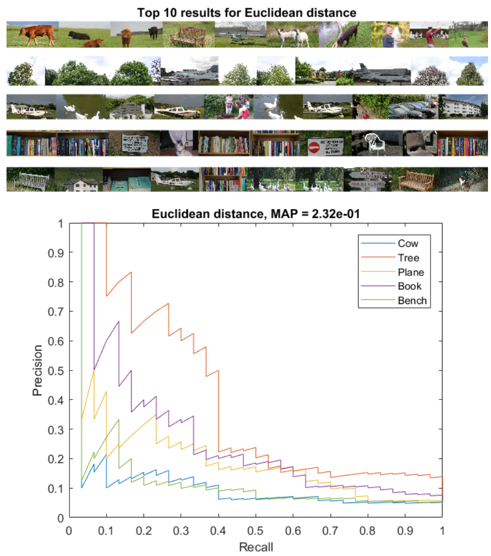

21. Edge Orientation Histogram results for Euclidean distance, 4 columns 4 rows and Q=256



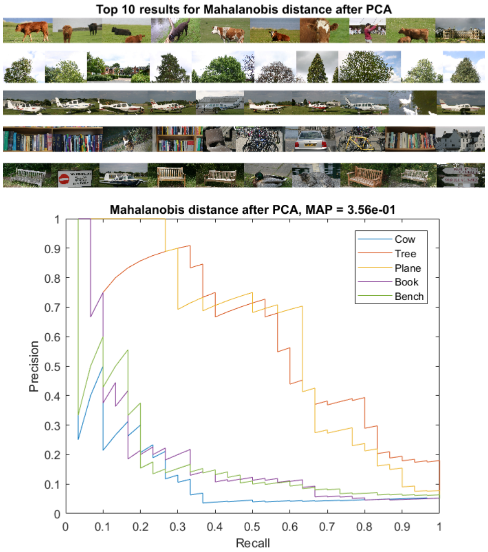

22. Edge Orientation Histogram results for Mahalanobis distance, 4 columns 4 rows and Q=256 after PCA



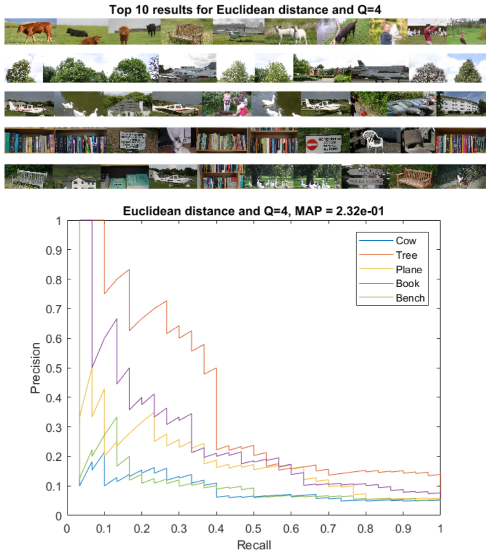

23. Colour Grid with Edge Orientation Histogram results for Euclidean distance, 4 columns 4 rows and Q=256



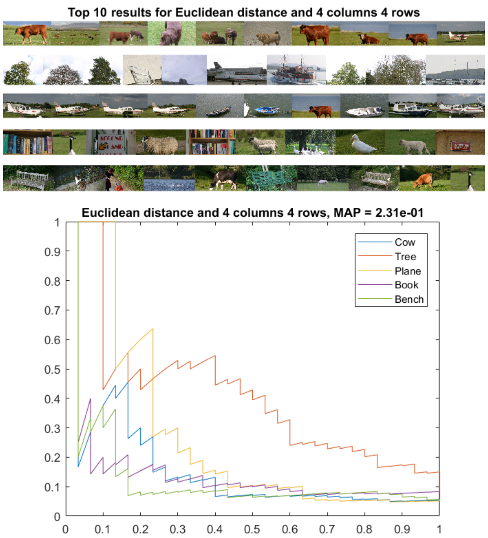

24. Colour Moment Results for Euclidean distance



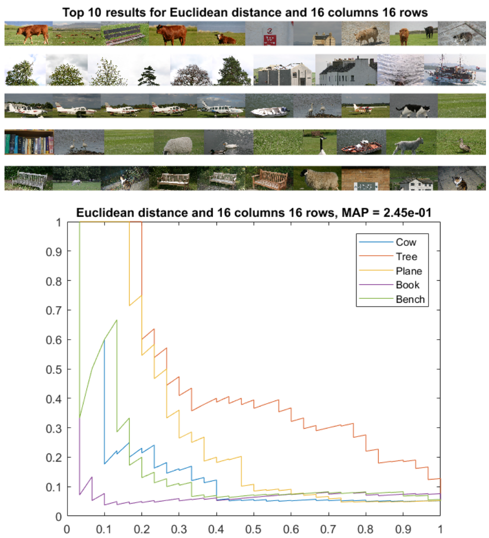

25. Colour Moment Results for Mahalanobis distance after PCA




26. Global Colour Histogram with Colour Moment Results for Euclidean distance and Q=4




27. New Technique Results for Euclidean distance and 4 columns 4 rows




28. New Technique Results for Euclidean distance and 16 columns 16 rows

# 5 Conclusions

The image descriptors' efficiency is measured not only by considering their ability to discriminate images, but also by taking into account their compactness. Several conclusions were derived from the experimental results detailed in section 3 of this document.

The global colour histogram technique has its highest MAP for Q=4 compared to Q=2 and Q=16. Therefore, a higher quantisation score does not ensure better performance, and the optimal quantisation level needs to be evaluated and found for each particular system through an in-depth analysis. In addition, the classification using Bray Curtis and L1 norm distance gives the best results, as opposed to the Euclidean distance, which yields one of the lowest MAP. This could be due to distance measures such as L1 norm producing sparser solutions than L2 norm, which can be beneficial in high-dimensional problems.

The colour grid technique presents both higher and lower MAP scores than the global colour histogram for different parameters and performs slightly better with a gridding of 16 columns 16 rows compared to 4 columns 4 rows, but this difference is almost negligible. The lower MAP scores of this technique compared to the global colour histogram are due to the effects of considering spatial information against not considering it. For instance, if the query image shows a cow on the left, the global colour histogram descriptors for all the cow images will be very similar, whereas the colour grid has a high change of not classifying an image with a cow on the right as similar to the query.

The edge orientation histogram technique has significantly higher MAP values than the previous techniques. This is true especially for the tree and plane categories. The performance is concordant with the fact that these images feature an object against the sky with very strong edges, as opposed to images from the bench category, in which the colour of the objects in easily confused with the background. Moreover, the edge orientation histogram technique presents its peak accuracy at 4 columns, 4 rows and Q=256 from the combinations analysed. For higher angular quantisation levels, the system performs better. This is due to the fact that very small differences in the orientation of the edges are detected, and the shape of the trees and planes featured on the dataset are very similar. Therefore, coarse gridding and high angular quantisation levels are recommended for the edge orientation histogram.

The colour grid with edge orientation histogram technique presents a higher accuracy than the colour grid alone but a lower accuracy than the edge orientation histogram technique. This is due to the spatial colour information being different for objects in the same category. For example, the pictures that contain a black cow will not be considered equal to the query that contains a brown cow in terms of colour, but they will in terms of shape. Hence, analysing the shape only yields a higher result in these situations than combining both. The lower MAP value is due to the fact that the MAP is the mean of the AP values for all the queries and even though the colour grid with edge orientation histogram descriptor performs well for classes such as trees is not accurate for classes such as cows.

The colour moment descriptor technique shows its highest MAP when computing PCA and using the Mahalanobis distance. This is true especially for the plane and tree clases, which is concordant with the fact that moment descriptors take into account not only colour but also shape information. To illustrate this, the cows images have a much less complex shape i.e less strong edges than planes, thus it is expected for the moment descriptor technique to be less accurate for the former.

The global colour histogram combined with the moment descriptor has a matching accuracy to the colour moment descriptor used independently. Therefore, in this particular situation, combining both colour descriptors does not increase performance. Additionally, this descriptor's accuracy matches that of the colour grid for coarse gridding. Therefore, this technique could potentially be used as a less computationally expensive alternative to the colour grid technique when using large grids to analyse the image.

The new descriptor has a better performance than the colour grid for the cow class, but performs lower for the plane, book and tree classes. This indicates that for images in which objects are large and of uniform colours, finding the colour values at several key points in the image could produce the same results as analysing every point in the image, but with a significantly lower computational expense. To illustrate this, to perform visual search on a set of images that show either a sand beach or a rock beach, the global colours could be very similar depending on the shades of the sand and rocks, so a global colour histogram would not be precise enough. Since the picture will also not have many strong edges, the best approach is to use a spatial colour detector. Since the different coloured areas are quite large, the new technique would produce precise results without the need to perform the large number of computation operations associated with the colour grid.

Overall the PCA results measured with the Mahalanobis distance produce a similar result to the standard results. The percentage of eigenvalues kept was chosen independently for each technique and were generally in the 90% percentile. This percentile was chosen to be high enough that the information is preserved i.e Euclidean distance yields the same results, but low enough that the data is projected into a lower-dimensional space.

In general, the classifiers perform best with images that represent trees and worse with images that feature benches, as shown by the different PR curves. This could be due to the tree images presenting very strong edges and colour contrasts i.e blue sky against green leaves, as opposed to the pictures containing benches, which tend to merge with the forest background. Moreover, the benches images have similar colour to those images featuring cows i.e green background and brown object colours, and are therefore easily confused by the classifiers. The different distance measures produce comparatively similar results, except for the L3 norm measure, which yields a very low accuracy and is therefore not recommended for image classification problems of this kind. The most efficient technique is the Edge Orientation Histogram combined with Euclidean distance for the highest quantisation levels.

# 6 Further Improvements to the System

To conclude, in order to improve the visual search system, the dataset could be divided into a training set and a test set following the supervised classification method. This would provide significantly more accurate test results and evaluate the system's ability to generalise its learned patterns. Additionally, the testing process should incorporate translated, rotated and scaled images in order to further analyse the techniques' accuracy and to determine whether they are robust i.e affine invariant.

# References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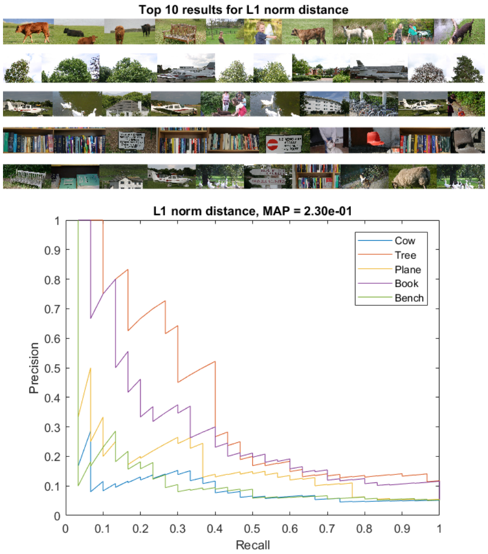
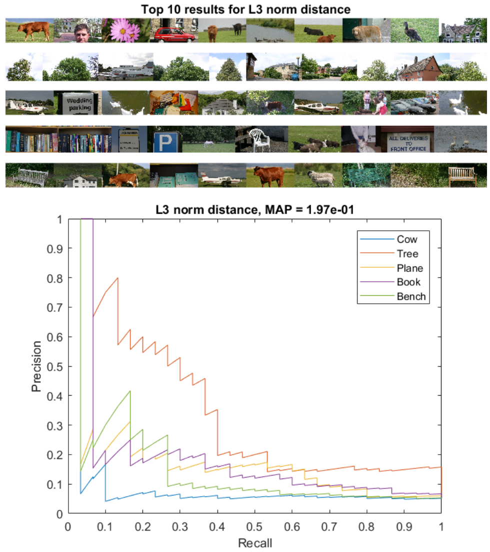
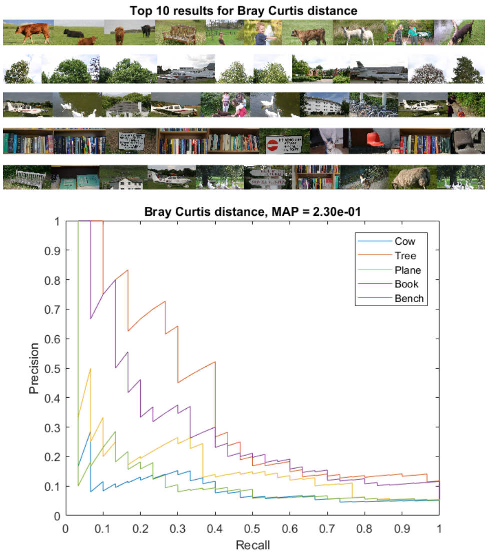
# A Appendix



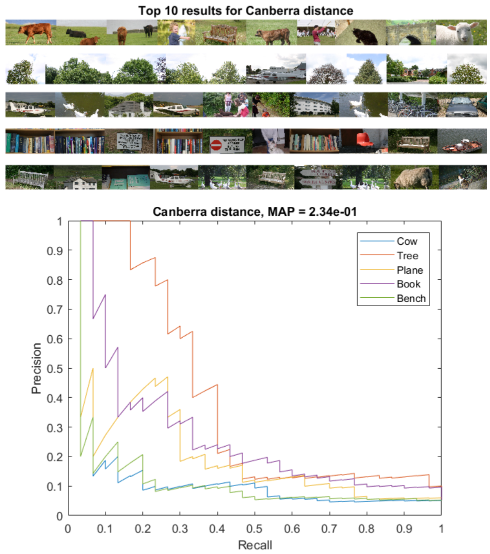

1. Colour Moment results for L1 norm distance



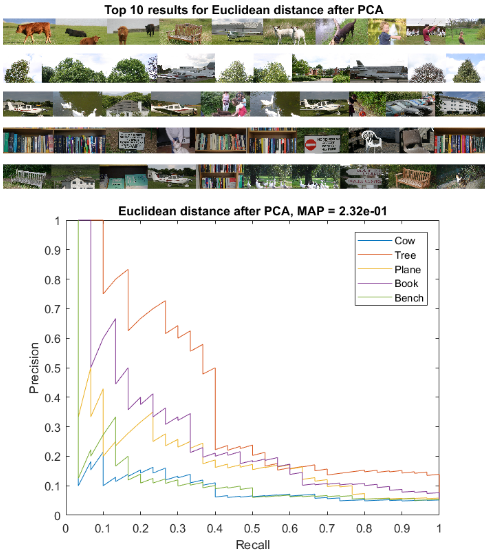

2. Colour Moment results for L3 norm distance



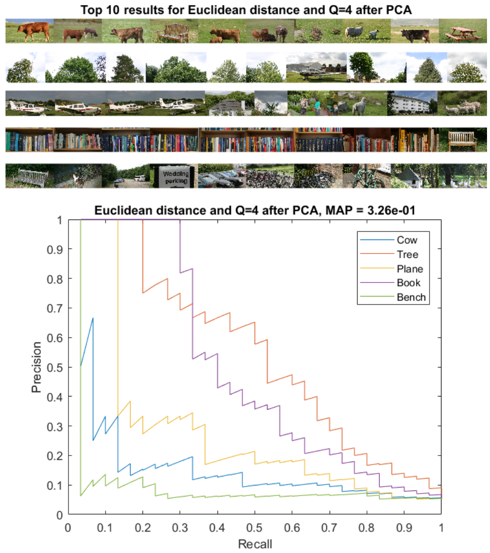

3. Colour Moment results for Bray Curtis distance



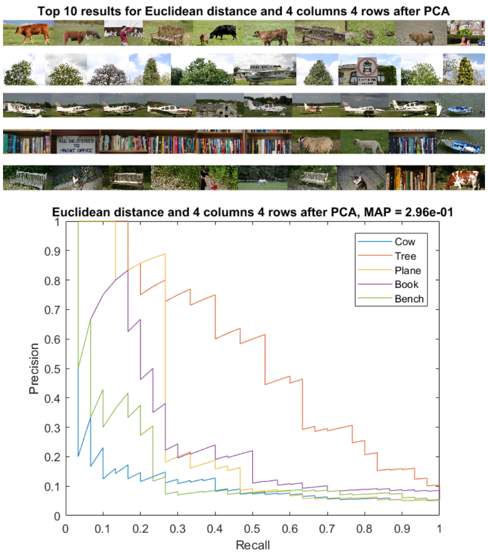

4.Colour Moment results for Canberra distance



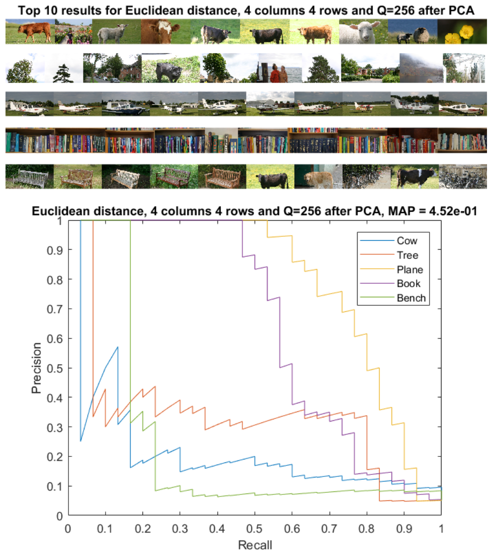

5. Colour Moment results for Euclidean distance after PCA




6. Global Colour Histogram results for Euclidean distance and Q=4 after PCA




7. Colour Grid results for Euclidean distance and 4 columns 4 rows after PCA




8. Edge Orientation Histogram Colour Grid results for Euclidean distance, 4 columns 4 rows and Q=256 after PCA