Feature Re-weighting in Content-Based Image Retrieval

Gita Das¹, Sid Ray¹, and Campbell Wilson²

¹ Clayton School of Information Technology
Monash University
Victoria 3800, Australia
{Gita.Das, Sid.Ray}@csse.monash.edu.au

² Caulfield School of Information Technology
Monash University
Victoria 3800, Australia
Campbell.Wilson@csse.monash.edu.au

Abstract. Relevance Feedback (RF) is a useful technique in reducing semantic gap which is a bottleneck in Content-Based Image Retrieval (CBIR). One of the classical approaches to implement RF is feature re-weighting where weights in the similarity measure are modified using feedback samples as returned by the user. The main issues in RF are learning the system parameters from feedback samples and the high-dimensional feature space. We addressed the second problem in our previous work, here, we focus on the first problem. In this paper, we investigated different weight update schemes and compared the retrieval results. We proposed a new feature re-weighting method which we tested on three different image databases of size varying between 2000 and 8365, and having number of categories between 10 and 98. The experimental results with scope values of 20 and 100 demonstrated the superiority of our method in terms of retrieval accuracy.

1 Introduction

The selection of features e.g. colour, shape, colour-layout etc. and their proper representation e.g. colour histogram, statistical moments etc. are very important for good system retrieval. However, the low level features (e.g. colour, shape) used to represent an image do not necessarily represent the high level semantics and human perception of that image. A solution towards this problem is human intervention in terms of Relevance Feedback [1], [2], [3]. For a given query, the system first retrieves a set of ranked images according to a similarity metric, which represents the distance between the feature vectors of the query image and the database images. Then the user is asked to select the images that are relevant or irrelevant (or non-relevant) to his/her query. The system extracts information from these samples and uses that information to improve retrieval results. A revised ranked list of images is then presented to the user. This process continues until there is no further improvement in the result or the user is satisfied with the result. In classical approach, there are mainly two ways to implement RF
namely, query updating and feature re-weighting. In query updating method, the components of the query vector are updated using the average of component values of all relevant samples so that the new query point moves towards the centre of relevant class. In feature re-weighting, the weight factors in the similarity measure are modified using relevant samples. The essence of feature re-weighting is to put more weights on the feature components that discriminate well between relevant and non-relevant images and thus enhances retrieval and to put less weights for the ones that do not help retrieval. Feature re-weighting is found to be very suitable for large size databases and high dimensional feature space [8]. Also, this method is simple to implement and produces fairly good retrieval. However, in order to improve retrieval accuracy we need to use the feedback samples carefully and intelligently. In MARS system [4], they used the inverse of standard deviation of the feature component values for the relevant samples. Most of the work reported in the literature used only relevant samples [5], [6], [7]. In [8], Wu and Zhang proposed a discriminant factor that determines the ability of a feature component in separating relevant images from the irrelevant ones. They showed improvement over the MARS system which used only relevant images. Inspired by their work, we propose a modified weight factor that demonstrated significant improvement over the method in [8]. Both of the query update and the feature re-weighting approaches are based on vector model which originally were used in text retrieval [1]. We used a combination of both methods. We experimented with several weight updating schemes to re-shape the similarity measure and compared the retrieval results.

Sections 2 and 3 describe the proposed approach and experimental results respectively. Section 4 contains conclusions and future directions.

2 Methodology

For rest of the paper, we used the following nomenclature:

\[ N: \] Number of images in the database
\[ C: \] Number of semantic categories in the database
\[ N_r: \] Scope i.e. the number of top retrieved images returned to the user
\[ Q, I: \] Query image and Database image respectively
\[ k: \] Number of iterations in RF
\[ M: \] Number of components in the feature vector
\[ w_i^k: \] weight factor for \( i^{th} \) feature component in \( k^{th} \) iteration.

### 2.1 Feature Representation

In [9], we proposed a compact feature representation based on the elements of Colour Co-occurrence Matrices (CCM) in Hue, Saturation, Value (H,S,V=16,3,3) colour space. We chose HSV colour model as it is known to be perceptually uniform. A Colour Co-occurrence Matrix represents how the spatial correlation of colour changes with distance i.e. pixel positions [10]. So, unlike colour histogram, colour co-occurrence matrix provides spatial information of the image.