1. INTRODUCTION

Managing multimedia databases requires the ability to retrieve meaningful information from the digital data, in order to help users find relevant multimedia data more effectively and to facilitate better ways of entertainment.

Motivated by a large number of requirements and applications such as sport highlighters, movie recommenders, image search engines, and music libraries, multimedia retrieval and semantic detection have become very popular research topics in recent years (Lew, Sebe, Djeraba & Jain, 2006; Shyu, Chen, Sun & Yu, 2007; Snoek & Worring, 2008). The general steps for supervised content-based multime-
dia retrieval consist of the segmentation of the multimedia data (i.e., detecting the basic units for processing), the representation of the multimedia data (i.e., extracting low-level features per unit), the model training using the low-level features, and the classification of the testing data using the trained model.

The most frequently used features for image retrieval are low-level features such as color, texture, and shape (Datta, Joshi, Li & Wang, 2008); while for video retrieval, the features are these visual features as well as some low-level audio and motion features (Lew, Sebe, Djeraba & Jain, 2006). One of the biggest challenges of multimedia retrieval is that it is hard to bridge the semantic gaps between the low-level features and the high-level features/concepts. Traditionally, these low-level features are considered contributing equally to the models, and the models are trained by using all the features they are provided. Later, the models are required to have the ability to select the features that better represent a certain concept class. In this manner, the features are selected before the model training process, and hence the models do not necessary benefit from the feature selection process (Lin, Ravitz, Shyu, & Chen, 2008; Liu & Motoda, 1998). From another point of view, the importance of the features is not considered equally anymore, but is considered as “good” or “bad” while performing the feature selection.

### 1.1 Weighted Features

The feature weighting gets more and more attentions from the researchers recently, since the contributions of different features may not be the same and it is very limited to discriminate the features as either selected ones or non-selected ones. The simplest method for feature weighting is manually set the weight values to various features. In Vadivel, Majumdar and Sural (2004), the fixed weights were given to the color and texture features on a large database of images. Different weights were experimented to 28,000 images and the best results appeared when the texture feature’s weight was from 0.1 to 0.2. Some other methods based on the mutual information, gain ratio, odds ratio, and term strength were reviewed in Pekar, Kakoska and Staab (2004). In addition, the authors proposed a feature weighting strategy for word retrieval, which combined the discriminative weights of a feature with each of its characteristic weights. The improved results showed that feature weighting before classification reflected how much the particular feature revealed about class membership of the instances.

An image retrieval model with weighted features based on relevance feedback was proposed by Kim et al. (2008). The annotation of an image was first done by using keywords, and then the confidence level of the keywords was modified in response to the user’s feedback. The discrimination power was used to represent how well the positive and negative images were distinguished when the images were re-ranked according to the visual features. The weight of a visual feature was simply calculated as the normalized discrimination power of that feature. In Ziou, Hamri and Boutemedjet (2009), a content-based image retrieval model with probability-based feature weighting was presented. A hybrid probabilistic framework adopted the generalized Dirichlet mixture and maximum likelihood to accurately estimate the statistical model of the data. The idea was under the assumptions that the relevance of different features is not the same for a given node, and a relative relevance of the features is sufficient to discriminate between nodes. Therefore, if a feature is irrelevant, then its weight should be small and its contribution in the indexing and retrieval should be weak. Another statistical measure based feature weighting method was introduced in Wakabayashi, Pal, Kimura and Miyake (2009). The Fisher ratio (F-ratio) was defined as the ratio of the between-class variance and the within-class variance and was used as the weight of the shape character. The higher the F-ratio is, the more useful information is to discriminate the similar classes the feature is contained. The experimental results of similar shape characters of different scripts showed the ability of the weighting scheme to
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