Chapter 2
Weighted Association Rule Mining for Video Semantic Detection

Lin Lin
University of Miami, USA

Mei-Ling Shyu
University of Miami, USA

ABSTRACT

Semantic knowledge detection of multimedia content has become a very popular research topic in recent years. The association rule mining (ARM) technique has been shown to be an efficient and accurate approach for content-based multimedia retrieval and semantic concept detection in many applications. To further improve the performance of traditional association rule mining technique, a video semantic concept detection framework whose classifier is built upon a new weighted association rule mining (WARM) algorithm is proposed in this article. Our proposed WARM algorithm is able to capture the different significance degrees of the items (feature-value pairs) in generating the association rules for video semantic concept detection. Our proposed WARM-based framework first applies multiple correspondence analysis (MCA) to project the features and classes into a new principle component space and discover the correlation between feature-value pairs and classes. Next, it considers both correlation and percentage information as the measurement to weight the feature-value pairs and to generate the association rules. Finally, it performs classification by using these weighted association rules. To evaluate our WARM-based framework, we compare its performance of video semantic concept detection with several well-known classifiers using the benchmark data available from the 2007 and 2008 TRECVID projects. The results demonstrate that our WARM-based framework achieves promising performance and performs significantly better than those classifiers in the comparison.

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 multimedia 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

Related Content

Information Retrieval Technologies and the "Realities" of Music Information Seeking
Charilaos Lavranos, Petros Kostagiolasand Joseph Papadatos (2016). *Experimental Multimedia Systems for Interactivity and Strategic Innovation (pp. 102-121).*
www.irma-international.org/chapter/information-retrieval-technologies-and-the-realities-of-music-information-seeking/135125

Bare Nothingness: Situated Subjects in Embodied Artists' Systems
Eleanor Dareand Elena Papadaki (2016). *Experimental Multimedia Systems for Interactivity and Strategic Innovation (pp. 16-48).*
www.irma-international.org/chapter/bare-nothingness/135122

Automated Filtering of Eye Movements Using Dynamic AOI in Multiple Granularity Levels
Gavindya Jayawardenaand Sampath Jayarathna (2021). *International Journal of Multimedia Data Engineering and Management (pp. 49-64).*
www.irma-international.org/article/automated-filtering-of-eye-movements-using-dynamic-aoi-in-multiple-granularity-levels/271433

Object-of-Interest Retrieval in Social Media Image Databases for e-Crime Forum Detection
Xinpeng L. Liao, Pradip Chitrakar, Chengcui Zhangand Gary Warner (2015). *International Journal of Multimedia Data Engineering and Management (pp. 32-50).*
www.irma-international.org/article/object-of-interest-retrieval-in-social-media-image-databases-for-e-crime-forum-detection/132686

Collaborative Work and Learning with Large Amount of Graphical Content in a 3D Virtual World Using Texture Generation Model Built on Stream Processors
Andrey Smorkalov, Mikhail Fominykhand Mikhail Morozov (2014). *International Journal of Multimedia Data Engineering and Management (pp. 18-40).*
www.irma-international.org/article/collaborative-work-and-learning-with-large-amount-of-graphical-content-in-a-3d-virtual-world-using-texture-generation-model-built-on-stream-processors/113305