Expert Systems with Applications 41 (2014) 6611–6621

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Study of image retrieval and classification based on adaptive features using genetic algorithm feature selection

Chuen-Horng Lin [a,*], Huan-Yu Chen [b], Yu-Shung Wu [a]

[a] Department of Computer Science and Information Engineering, National Taichung University of Science and Technology, No. 129, Sec. 3, Sanmin Rd., Taichung, Taiwan, ROC
[b] Department of Electrical Engineering, National Chung Hsing University, No. 250 Kuo Kuang Rd., Taichung, Taiwan, ROC

ARTICLE INFO

Article history:
Available online 6 May 2014

Keywords:
Color feature
Texture features
Genetic algorithms
Feature selection
Support vector machine

ABSTRACT

This paper proposes a *genetic algorithm feature selection* (GAFS) for image retrieval systems and image classification. Two texture features of *adaptive motifs co-occurrence matrix* (AMCOM) and *gradient histogram for adaptive motifs* (GHAM) and color feature of an *adaptive color histogram for K-means* (ACH) were used in this paper. In this paper, the feature selections have adopted *sequential forward selection* (SFS), *sequential backward selection* (SBS), and *genetic algorithms feature selection* (GAFS). Image retrieval and classification performance mainly build from three features: ACH, AMCOM and GHAM, where the classification system is used for two-class SVM classification. In the experimental results, we can find that all the methods regarding feature extraction mentioned in this study can contribute to better results with regard to image retrieval and image classification. The GAFS can provide a more robust solution at the expense of increased computational effort. By applying GAFS to image retrieval systems, not only could the number of features be effectively reduced, but higher image retrieval accuracy is elicited.

1. Introduction

With the rapid development of information technology and multimedia technology, many electronic imaging equipments have become popular, resulting in a growing amount of multimedia information. Various image collections and databases have led to the rapid growth of the image retrieval field, a challenging and expanding research area. Thus, determining how to effectively and efficiently retrieve a desired image from a constantly growing image database has become an important issue.

Traditional image retrieval systems are based on the features of the original data (Gong, Zhang, Chuant, & Skauuchi, 1994; Gu, Panda, & Haque, 2001), such as: file name, note title, keyword and indexing icon. When applied to large scale image databases, these features become troublesome, time-consuming and even inadequate in regard to describing image contents. To improve the accuracy of the image retrieval systems, it is important to have a proper image feature set that describes the precise contents of an image. The more suitable the image features that are set, the higher the retrieval accuracy that results! Similarity computation step models employ image similarity based on combinations of various features extracted from images. In recent years, image retrieval systems have been based on image contents which are most commonly used, i.e. color, texture, spatial relationships, shape and others. The focus has also been narrowed in developing new techniques, wherein effective retrieval and browsing of large digital image libraries is based on automatically derived imagery features.

Many feature-based image retrieval systems have been proposed (Swain & Ballard, 1991; Rui & Huang, 1999; Brnuelli & Mich, 2001; Chun, Seo, & Kim, 2003; Ko & Byun, 2005; Hurtut, Gousseau, & Schmitt, 2008; Lin, Chen, & Chan, 2009; Lin & Lin, 2010; Haralick, Shanmugam, & Dinstein, 1973; Huang & Dai, 2003; Jhanwar, Chaudhurib, Seetharamanc, & Zavidovique, 2004; Moghaddam, Khajoie, Rouhi, & Tarzjan, 2005; Hafiane & Zavidovique, 2008; Liu & Yang, 2008; Wei, Li, Chau, & Li, 2009). For instance, colors (Swain & Ballard, 1991; Rui & Huang, 1999; Brnuelli & Mich, 2001; Chun et al., 2003; Ko & Byun, 2005; Hurtut et al., 2008; Lin et al., 2009; Lin & Lin, 2010), textures (Lin et al., 2009; Lin & Lin, 2010; Haralick et al., 1973; Huang & Dai, 2003; Jhanwar et al., 2004; Moghaddam et al., 2005; Hafiane & Zavidovique, 2008; Liu & Yang, 2008), spatial relations (Hurtut et al., 2008; Lin, Chan, Chen, Huang, & Chang, 2011) and shapes (Wei et al., 2009) have been extensively applied to the task of image retrieval but the results have garnered limited effects on discrimination. Color attribute analysis (Swain & Ballard, 1991; Rui & Huang, 1999; Brnuelli & Mich, 2001; Chun et al., 2003; Ko & Byun,

* Corresponding author. Tel.: +1 886 4 22195502.
E-mail addresses: linch@nutc.edu.tw (C.-H. Lin), d9564104@mail.nchu.edu.tw (H.-Y. Chen), iay128@gmail.com (Y.-S. Wu).

http://dx.doi.org/10.1016/j.eswa.2014.04.033
0957-4174/

2005; Hurtut et al., 2008; Lin et al., 2009; Lin & Lin, 2010) has proven to be very successful with regard to retrieving images. The color histogram (Swain & Ballard, 1991) is a common technique used in image retrieval systems. The advantages of a color histogram include simple procedures and quick calculations. The texture feature (Lin et al., 2009; Lin & Lin, 2010; Haralick et al., 1973; Huang & Dai, 2003; Jhanwar et al., 2004; Moghaddam et al., 2005; Hafiane & Zavidovique, 2008; Liu & Yang, 2008) based approach to gray levels is one of the most popular among image retrieval systems. Although there is no formal definition for describing texture, humans intuitively use vague textural properties like coarseness, fineness, orientation or regularity. Color features are commonly used in image retrieval systems which then combine texture, spatial relationships and shape features to the application.

Huang and Dai (2003) proposed a texture based image retrieval system that combines the wavelet decomposition and gradient vector. The image retrieval system introduced in N. Jhanwar et al. (2004) is based on motif co-occurrence matrix (MCM) and converts the difference between pixels into a basic graphic while computing the probability of its occurrence in the adjacent area as an image feature. Lin et al. (2009) proposed a smart content-based image retrieval system based on color and texture features. In addition, a feature selection technique was also brought forward to select optimal features to not only maximize the detection rate but also to simplify the computation of image retrieval. Lin and Lin (2010) proposes three image features for use in an image retrieval system based on an adaptive color histogram and texture features. The first image feature is based on color distribution. The second and third image features are based on color and texture features, respectively.

For these image retrieval systems, the feature number and image variety in a database proliferate, and the discriminative power of simple features becomes insufficient. Therefore, the more advanced systems use combinations of features with the relative importance of each feature either fixed by the user, or interactively inferred by the system through the relevance feedback. These systems allow arbitrarily complex combinations of image features to be used regarding the choice of features or their relative importance. However, the optimal combination of image features is inferred for a given query image, and most systems are designed to deal with global image features, which apparently do not comprise the best choice. These features can be fixed or changeable. The selection of these features depends on the database to a great extent.

Feature selection is a problem that has to be addressed in artificial intelligence. The main issues in developing feature selection techniques are choosing a small feature set in order to reduce the cost and running time of a given system, as well as achieving an acceptably high recognition rate. However, while it is generally believed that a better image recognition effect can be achieved with more feature descriptors used, this is not absolutely true. Not all features are helpful for image recognition. Notably, ill features are actually interfering signals and cause a drop in the recognition rate, specifically if the effect of the ill features exceeds those of the effective ones. Thus, for a finite and usually limited number of training patterns, keeping the number of features as small as possible is in line with our desire to design classifiers with good generalization capabilities.

Many feature selection techniques from a larger set of possible features have been proposed. A feature subset selection algorithm based on branch using a bound technique is developed to select the best subset of *m* features from an *n*-feature set by Narendra and Fukunaga (1977). Among the feature selection methods of the speculative multiple solutions in *statistical pattern recognition* (SPR), one of the most representative is the concept of *genetic algorithms* (GA). The basic theory of GA is based on the Darwinian theory of evolution, i.e., the survival of the fittest, and follows natural evolutionary law. This method can be applied towards solving optimization problems. Siedlecki and Sklansky (1989) integrated GAs and the *k-nearest neighbor* (KNN) classifier towards solving feature selection problems. Using the fitness function assessment of KNN classifiers in the environment, the criterion could be selected for the best combination of the features. Whitney (1971), proposed two feature selection methods: *sequential forward selection* (SFS) and *sequential backward selection* (SBS). Pudil, Ferri, Novovicova, and Kittler (1994) developed the idea that floating search algorithms are presented and modified into a more compact form thus facilitating their direct comparison with the *plus l-take away r* search method.

Notably, image classification is an important component of digital image analysis. Two main classification methods are supervised classification and unsupervised classification. Supervised classification is the essential tool used for extracting quantitative information from the image. Unsupervised classification does not have the foreknowledge of the classes and mainly uses clustering algorithms to classify image data. For texture image classification, Ojala, Pietikainen, and Maenpaa (2002) proposed the concept of a *local-binary-pattern* (LBP) operator. The LBP operator primarily describes the texture in images and provides a theoretically simple and multi-resolution statistical method. Liao, Law, and Chung (2009) proposed features robust enough for image rotation; these exhibited less sensitivity to histogram equalization and noise.

The optimum adaptive features Lin and Lin (2010) derived can accurately describe not only gray texture images and color texture images, but also natural images, when applied to various image databases. Therefore, three image features from Lin and Lin (2010) are used in this paper. The first image feature is called an *adaptive color histogram for K-means* (ACH). The second and third image features are called *adaptive motifs co-occurrence matrix* (AMCOM) and *gradient histogram for adaptive motifs* (GHAM), respectively. The features adopted by this paper include ACH for the color information, AMCOM for the relationship between color and texture and GHAM for the AMCOM of an image.

This paper proposes adopting *sequential forward selection* (SFS), *sequential backward selection* (SFS) and *genetic algorithms feature selection* (GAFS). These methods choose a small feature set and improve the recognition rate. The combinations of features are used for the classification of a database image set, with image precision derived from image retrieval used to determine the fitness function. These methods search for the best combination in the next feature but cannot ensure that the method selected is the best combination.

The image features and retrieval will be introduced in Section 2.1. Feature selection will be introduced in Section 2.2. Section 2.3 describes the image classification system. Experiments and comparisons to other approaches are presented in Section 3. Conclusions are presented in Section 4.

2. The proposed method

First, this paper proposes two color and texture features, and the matching distance between the images. Next, the feature selections have adopted SFS, SBS and GAFS in this paper. Then, the integration of multiple features may certainly reduce retrieval and classification performance.

2.1. Image features and retrieval

The features of an image from Lin and Lin (2010) are used by this paper. Lin and Lin (2010) proposes three image features of