International Journal of Soft Computing 3 (2): 84-87, 2008
ISSN: 1816-9503

Feature Extraction and Selection for Image Retrieval

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Abstract: In this study feature extraction process is analyzed and a new set of edge features is proposed. A revised edge-based structural feature extraction approach is introduced. A principle feature selection algorithm is also proposed for new feature analysis and feature selection. The results of the PFA is tested and compared to the original feature set, random selections, as well as those from Principle Component Analysis and multivariate linear discriminant analysis. The experiments showed that the proposed features perform better than wavelet moment for image retrieval in a real world image database and the feature selected by the proposed algorithm yields comparable results to original feature setstudy better results than random sets.

Key words: Feature extraction, feature selection, content-based image retrieval, principle component analysis, discriminant analysis

INTRODUCTION

Image retrieval problem, can be regarded as a pattern classification problem, where each image is assumed-as ground truth-belongs to a specific class. Then query-by example is to find the class and return images within that class. Applications include medical image database retrieval, aerial/satellite image analysis and retrieval, etc., where the user is interested in some pre-defined targets such as tumors or vehicles.An example can be illustrated by the image in Fig. 1 as a query image submitted by the user, it is possible that the user is looking for cars, or the user is looking for autumn, or house, etc. In general this is the case for every image in the database, i.e., each image has multiple possible labels, or class memberships. We refer the retrieval process in this case as dynamic matching.

In this study we will discuss the feature extraction and selection process with the aforementioned characteristics of image retrieval problem in mind. For the image classification case, when some class labels are available, Multivariate Linear Discriminant Analysis (MLDA) is applied to transform the features into the Most Discriminating Feature space. If a reduced feature space is desired, it can only be done based on the results of sufficient trials of the relevance feedback process, so that a feature is deleted or ignored to a great extent only if it does not contribute in all or most of the dynamic weighting schemes (Fig. 2). Feature extraction is the process of creating a representation for, or a transformation from the original data. The scope of this study is depicted in Fig. 2 where the modules with a "*" are the emphasis of this study.

Fig. 1: An image of multiple objects

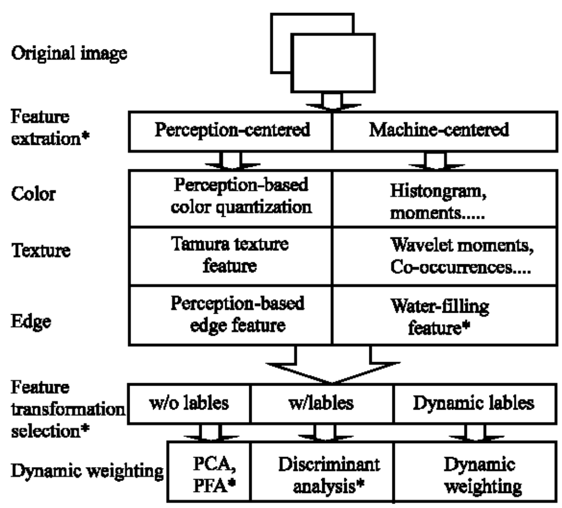

Fig. 2: Feature extraction

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EDGE-BASED STRUCTURE FEATURE EXTRACTION

In this study we use water-filling algorithm to extract edge/structural features. The advantages of this algorithm include efficiency it is a linear-time algorithm and effectiveness multiple features corresponding to different human perceptions can be extracted simultaneously (Tamura *et al*., 1978; Corman *et al*., 1979).

The water-filling algorithm: We propose an algorithm to extract features from the edge map directly without edge linking or shape representation. In this study, we use 4 connectivity for simplicity. The algorithm also assumes that thinning operation has been performed on the edge map so that all the edges are one pixel wide. To illustrate the algorithm, let's first consider the simple case of an 8 by 8 edge map with all the edge pixels connected (Fig. 3 shaded pixels are edge pixels). The algorithm will do a first raster scan on the edge map and start a traverse at the first edge pixel encountered that has less than 2 neighbors, i.e., start at an end point. In Fig. 3 the pixel with label "1" is the first end point encountered. The waterfront then flows along the edges in the order indicated by the numbers.

One can see that this algorithm can be regarded as a simulation of flooding of connected canal systems), hence the name water-filling algorithm. When there are more than one set of connected edges in the edge map, the algorithm will fill all the sets independently in sequential or in parallel. As water fills the canals (edges), various information are extracted, which are stored as the feature primitives. Feature vectors can then be constructed based on these feature primitives.

The time complexity of this algorithm is linear, proportional to the number of edge points in the image (Flickner *et al*., 1995).

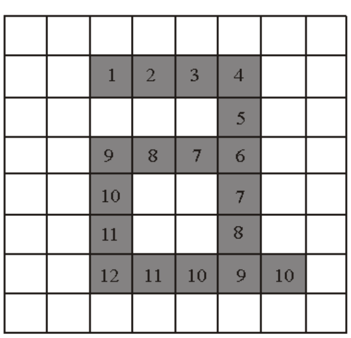

Fig. 3: Edge map with all edge pixels

Feature extraction

Feature primitives: We propose the concept of Feature primitives which are defined as the quantities associated with or calculated from an image that can serve as bases for constructing feature vectors, often through using their statistics or entropies. Feature primitives can be used as feature vector directly as well, but often they are not compact enough. For example, co-occurrence matrices are the feature primitives for the co-occurrences texture features, most of which are moments, correlationsstudy entropies (Haralich *et al*., 1973) and wavelet transform coefficients can be regarded as feature primitives for wavelet based texture features such as wavelet moments. In our case, we propose the following quantities as structural feature primitives.

Filling time: Filling time is the time for water to fill a set of connected edges. Using different starting pixels, the filling time can vary in a range of [t, 2t], where t is the minimum filling time among all possible selection of the starting pixels. To minimize the variation in filling time due to selection of starting pixels, we can impose additional constraints on the selection of starting pixels or choose different starting pixels and average the results. To achieve scaling invariance, normalize the filling time according to the image size.

Fork count: Fork count is the total number of branches the waterfront has forked during the filling of a set of edges.

Loop count: Loop count is the number of simple loops in a set of connected edges. Loop count is invariant to rotation.

Water amount: Water amount is the total amount of water used to fill up the set of edges in terms of number of pixels.

Horizontal (vertical) cover: Horizontal (vertical) cover is the width (height) of the rectangular bounding box of the set of edges.

Longest horizontal (vertical) flow: Longest horizontal (vertical) flow is the longest horizontal (vertical) edge in the set of connected edges. The final selection should depend upon the specific application, i.e., what information is important and most discriminative toward the classification.

Edge/structural feature formation: Based on the feature primitives, we can then construct edge/structural features from their statistics. In the following we discuss some examples with the emphasis on their meanings from a human perception point of view.

Max filling time and the associated forkcount: Max Filling Time (MFC) is defined as max{filling times}. MFT and FC are features most probably associated with a salient object in the image. The MFT conveys a rough measure of the size of this object, while the associated FC gives measure of complexity of the structure of the object.

Max fork count and the associated filling time: Similarly defined as MFT and FC, these are also features most probably associated with a salient object in the image. The MFT conveys a rough measure of the complexity of the object. This object may or may NOT be the same object as the previous one. GlobalLoopCount is defined as sum{loop counts}. MaxLoopCount is max{loop counts}. This feature vector can capture structural information such as the windows in the build images. Or can be used toward character detect and recognition applications.

Filling Time Histogram and the associated averaged Fork Count within each bin (FTH and FC): This is a global feature on all sets of connected edges in the edge map. It represents the edge map by the distribution of edge length. Noise or changing background with short edges may only affect part of the histogram, leaving the portion depicting the salient objects unchanged.

Water Amount Histogram (WAH): This is also a global feature with multiple components. It is another measure of the distribution in edge length or density.

FEATURE TRANSFORMATION AND SELECTION

For any handcrafted feature set, data-dependent analysis can always be carried out to select an optimal projection or transformation to best represent the information carried in the original feature set, or reduce the dimensionality with minimum information loss. When there is no label for the data, principle components analysis gives the best linear transform from the original feature set in terms of reconstruction errors. If class labels are (partially) available, then Multivariate Linear Discriminant Analysis (MLDA) gives the best linear transformation in terms of maximizing the ratio of inter-class scatter over in-class scatter, i.e., the MLDA vector has the most discriminating power among all linear transformations. The resulting transformation of PCA or MLDA is in general different. Here we propose a Principle Feature Selection algorithm for un-labeled data, i.e., this algorithm will output the subset of the features that will best represent original data (Gonzalez ans Woods, 1992).

Principle Component Analysis (PCA): Principle components are the projection of the original features onto the eigenvectors corresponds to the largest eigen values of the covariance matrix of the original feature set. Principle components provide linear representation of the original data using the least number of components with the mean-squared error minimized (Hu, 1962).

Principle Feature Analysis (PFA): Let X be a zero mean n-dimensional random feature vector. Let Σ be the covariance matrix of X. Let A be a matrix whose columns are the orthonormal eigenvectors of the matrix Σ, computed using the singular value decomposition of the Σ. The vector Vi corresponds to the i'th feature (variable) in the vector Xstudy the coefficients of Vi correspond to the weights of that feature on each axes of the subspace. Features that are highly correlated will have similar absolute value weight vectors. In order to find the best subset we will use the structure of these rows to first find the features which are highly correlated to each other and then choose from each group of correlated features the one which will represent that group optimally in terms of high spread in the lower dimension, reconstruction and insensitivity to noise. The reason for choosing the vector nearest to the mean is twofold. By choosing the principal features using this algorithm, we choose the subset that represents well the entire feature set both in terms of retaining the variations in the feature space and keep the prediction error at a minimum.

CONCLUSION

In this study we proposed a revised edge-based structural feature extraction approach by following guidelines obtained from summarizing the existing feature extraction approaches. A principle feature selection algorithm is also proposed for new feature analysis and feature selection. The results of the PFA is tested and compared to the original feature set, random selections, as well as those from Principle Component Analysis and multivariate linear discriminant analysis.

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