영상 검색 시스템을 위한 퍼지 논리 기반 특징 융합 기법

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Fuzzy Logic-based Feature Fusion Technique for Image Retrieval System

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Abstract

Image retrieval is one of the fundamental tasks in computer vision that involves searching and retrieving relevant images to a query from a database. It has applications in various domains, including image search engines and recommendation systems. For image retrieval, it is necessary to extract sufficiently large number of features from images to distinguish them in a high-dimensional space. However, there is a direct relationship between feature vector size and computational cost of comparing two feature vectors. Therefore, this work proposes a new feature fusion technique that combines fuzzy logic and color micro-structures to define an image in a high-dimensional feature space for retrieval applications. The simulation analysis shows that proposed fusion technique delivered up to 3% better precision score compared to the conventional techniques with a small computational overhead.

Ⅰ. Introduction

Image retrieval is one of the fundamental tasks in computer vision that involves searching and retrieving relevant images to a query from a large collection of images. It has applications in various domains, including online education, image search engines and recommendation systems.

In general, image retrieval algorithms can be divided into three groups [1], i.e., text-based, content-based and semantic-based algorithms. Text-based image retrieval techniques use keywords associated with images to find and retrieve a relevant image from the database. Such textual annotation is labor intensive task and it is often difficult to precisely describe an image in words. The content-based image retrieval (CBIR) techniques replace textual annotations with image feature descriptors such as color, texture, shape etc. Since such features cannot represent image semantics, semantic-based image retrieval techniques based on deep learning are proposed. However, the main challenge is the associated computational cost of running these algorithms, and their dependability on massive datasets to learn image representation.

This work proposes a CBIR scheme that incorporates a new feature fusion technique by combining fuzzy logic [2] with micro-structure descriptors [1] to define an image in a high-dimensional feature space. For a similarity comparison between template and query images, L1 distance was computed between their feature vectors as it is computationally simple, yet an efficient metric for the retrieval task [1].

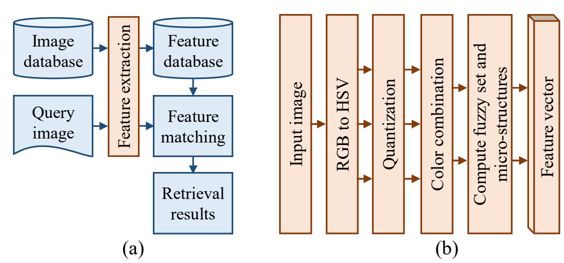


Fig. 1. Proposed image retrieval scheme. (a) is the overall framework and (b) is the feature extraction module.

Ⅱ. Proposed Method

Fig. 1. shows proposed image retrieval scheme, which consists of two main modules: feature extraction and feature matching modules as described below.

Feature Extraction: For feature extraction module, we propose a feature fusion technique that combines fuzzy logic [2] and color micro-structure descriptors [1] to describe an image in a high-dimensional feature space in the following steps:

1). Compute vectors $\mathbf{u}$ and $\mathbf{v}$ for quantization as

$$\begin{cases} \mathbf{u}_i^k = \mathbf{v}_{i-1}^k, \\ \mathbf{v}_i^k = \mathbf{v}_{i-1}^k + \dfrac{\max(C^k)}{b^k}, \end{cases} \tag{1}$$

where $k \in K = \{H, S, V\}$, $b^k \in \mathbf{b} = [b^H, b^S, b^V]$ is the quantization level, C^k is a HSV component, and $i =$

$[0,1,\dots,b^k-1]$. Furthermore, the initial values are chosen as $\mathbf{u}_0 = z < \min(C^k)$ and $\mathbf{v}_0 = \max(C^k)/b^k$.

2). Using vectors $\mathbf{u}$ and $\mathbf{v}$ quantize C^k as

$$\forall\{C^k > \mathbf{u}_i^k \wedge C^k \leq v_i^k\}: Q^k = i. \tag{2}$$

3). Combine the quantized components Q^k in a single-dimension plane as

$$L = b^S \times b^V \times Q^H + b^S \times Q^S + Q^V. \tag{3}$$

4). Generate a fuzzy set (A, μ_A) where A is a set containing the histogram of L i.e., $h(L)$, and $\mu_A: A \rightarrow [0,1]$ is the membership function that produces a fuzzy histogram as [2]

$$\boldsymbol{\phi} = \frac{A}{\max(A)}. \tag{4}$$

5). Compute the color micro-structures as following. First, find the number of neighbors each pixel $l \in L$ having the same value by using a function $f(l)$. Then, generate a vector $\mathbf{m}$ consisting the sum of neighbors for each symbol in L. This process is given as

$$\mathbf{m}_l = \mathbf{m}_l + f(l). \tag{5}$$

The color MSD feature vector $\boldsymbol{\varphi}$ is then defined as

$$\boldsymbol{\varphi} = \frac{\mathbf{m}}{N \times h(L)}, \tag{6}$$

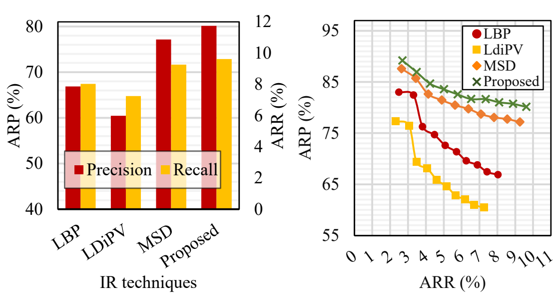
where, N is the total number of neighbors of a pixel $l \in L$. The final feature vector $\boldsymbol{\Phi}$ is a fusion of the feature vectors $\boldsymbol{\phi}$ and $\boldsymbol{\varphi}$ given by their concatenation as $\boldsymbol{\Phi} = \boldsymbol{\phi} \parallel \boldsymbol{\varphi}$. For all template images stored in the database, an M-dimensional feature vector $\boldsymbol{\Phi}_t$ is extracted and stored in the feature database.

Feature Matching: Let $\boldsymbol{\Phi}_q$ be the feature vector of a query image q, the goal of a feature matching function $\delta(\boldsymbol{\Phi}_q, \boldsymbol{\Phi}_t)$ is to find relevant images to q in template images $t \in T$ by comparing a distance between their feature vectors as

$$\delta(\boldsymbol{\Phi}_q, \boldsymbol{\Phi}_t) = \sum_{i=1}^{M} \left|\boldsymbol{\Phi}_{q(i)} - \boldsymbol{\Phi}_{t(i)}\right|. \tag{7}$$

Ⅲ. Simulation Results

In this section, we validate the performance of proposed image retrieval scheme on Coral-1K dataset [3]. The dataset consists of 1,000 color images of size 384×256 divided into 10 categories. For evaluation metrics, we used average retrieval precision (ARP) and recall (ARR), which respectively measures how many relevant images retrieved and how many relevant images are correctly identified. In simulations, proposed scheme was compared with three existing techniques such as LBP [4], LDiPV [5] and MSD [1].



(a) (b)

Fig. 2. Performance of proposed image retrieval scheme. (a) plots average precision and recall scores and (b) plots precision vs. recall curves.

In addition, the accuracy noise reduction module proposed in [6] was incorporated in all techniques for improved performance. Fig. 2. compares the retrieval performance of proposed scheme with conventional techniques. It can be seen that proposed method has ~3% better ARP score compared to other techniques as shown in Fig. 2. (a). Also, Fig. 2. (b) plots the precision vs. recall curves by varying the number of retrieved images that is, 3 to 12 images. The precision vs. recall curve of proposed system is smooth and further away from the origin as compared to existing techniques; therefore, showing better retrieval performance.

IV. Conclusion

This work proposed a new feature fusion technique that combined micro-structure descriptor with fuzzy logic to represent an image in a high-dimensional feature space for retrieval applications. Simulation analysis on Coral-1K dataset confirmed the efficiency of proposed scheme. Though our technique out performed existing techniques in terms of retrieval efficiency, its higher dimensional space makes the feature matching slower as compared to its counterparts. Therefore, in the future we are interested in addressing this issue by clustering the features.

ACKNOWLEDGMENT

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