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Image Retrieval with Feature Extraction: Survey and Discussions

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ABSTRACT
Image retrieval and classification is very critical task in computer vision. The efficiency of image classification decides the performance and retrieval of search engine. The process of classification basically depends on features of image. The feature of image basically content three lower content features such as color, texture and dimensions of image used during the process of classification. Researchers used data mining, classification and neural network technique for the classification of image. In this paper we present the review of image classification techniques based on their features. In future we develop a model for image classification and improved the result of image classification and retrieval than previous work.

Keywords:- Image Processing, Feature Extraction, Neural Network, Deep Learning.

INRODUCTION

In the context of today's scenario the use of digital technologies produces a lot of digital images. Large collections of images are becoming available to the public, from photo collection to web pages, or even video databases. Since visual media requires large amounts of memory and computing power for processing and storage, there is a need to efficiently index and retrieve visual information from image database [1]. In recent years, image classification has become an interesting research field in application.

Efficient indexing and retrieval of large number of color images, classification plays an important and challenging role [2]. Digital images can be formed by a variety of devices like digital scanners, cameras, co-ordinate measuring machines, digital video recorders, digital synthesizers and airborne radars. Among the various media types, images are of prime importance. Not only it is the most widely used media type besides text, but it is also one of the most widely used bases for representing and retrieving videos and other multimedia information.

The ability to identify the objects present in an image or scene is one of the most basic requirements when it comes to interacting with ones environment. While it seems completely effortless with humans and in fact most animals, trying to teach computers to see and also understand" what they are seeing has proven extremely difficult. The key to understanding visual scenes are three closely related sub-problems. The easiest one will be called classification in the following. For classification, the one dominant object in a given image should be determined and labelled. The next more demanding task is object localisation: In addition to labelling the dominant object, it also needs to be localised in the image, usually by determining a bounding box around the image region that is occupied by the object. The difficulty of this task again increases if not only one but all objects in an image need to be labeled and multiple objects of the same category can appear in one image, This task is called object detection.

Image features refer to the information collected from images that can uniquely identify the image or can be used for further processing. Broadly, image features can be classified into general features and domain-specific features [5]. General features, such as color and texture are applicable to all image data and do not depend on the application being considered. Domain-specific features on the other hand, are specific to the application at hand, such as, minutiae in fingerprints. In this work, general features are explored and used in different applications that require image classification.

Based on the locality of features, image features can be categorized into [6]: Local features and Global features, Local features are the patterns in images that differ from its immediate neighborhood. These features are extracted from a patch in the image and are useful in applications such as object recognition. Some examples of local features are Shape Invariant Feature Transform (SIFT), Local Binary Pattern (LBP), and Speeded up Robust Features (SURF). The Global features represent the whole image. These features are extracted considering the whole image as one patch/object and are useful in applications such as image retrieval and image classification, where a rough segmentation of objects is available. Some examples of global features are Histogram Oriented Gradient (HOG) and Shape Matrices.

The content based image classification systems can be widely classified as color, texture, shape, motion etc. color based image classification is an important alternative and complement to traditional text-based image searching and can greatly enhance the accuracy of the information being returned [12]. It aims to develop an efficient visual- Content-based technique to search, browse and classify relevant images from large-scale digital image collections. Most proposed CBIC techniques automatically extract low-level features (e.g. color, texture, shapes and layout of objects) to measure the similarities among images by comparing the feature differences. Supervised classification is appropriate when we want to identify relatively few classes, when we have selected training sites that can be verified with ground truth data, or when we can identify distinct, homogeneous regions that represent each class [14]. Whereas Supervised classification is usually appropriate when we want to identify relatively few classes, when we have selected training sites that can be verified with ground truth data, or when we can identify distinct, homogeneous regions that represent each class.

II CLASSIFICATION

Image classification is basically the task of classifying the number of images into (semantic) categories based on the available training data. The objective of digital image classification procedure is to categorize the pixels in an image into land over cover classes [12]. The output is thematic image with a limited number of feature classes as opposed to a continuous image with varying shades of gray or varying colors representing a continuous range of spectral reflectance [11]. The range of digital numbers in different bands for particular features is known as a spectral pattern or spectral signature. A spectral pattern can be composed of adjacent pixels or widely separated pixels. Digital image classification technique can generally be classified into two types: Unsupervised classification Techniques and Supervised classification Techniques [12]. Classification approaches deal poorly on content based image classification tasks being one of the reasons of high dimensionality of the feature space. A common approach to image classification involves addressing the following three issues: (i) image features: how to represent the image, (ii) organization of feature data: how to organize the data, and (iii) classifier: how to classify an image.

III RELATED WORK

In image retrieval the approach of using content based image retrieval tasks being one of the reasons of high dimensionality of the feature space. Color image retrieval is done on features extracted from histograms of color components. The benefit of using color image histograms are better efficiency, and insensitivity to small changes in camera view-point i.e. translation and rotation. There are two types of ants that have different search strategies and refreshing mechanisms. The stochastic ants identify new categories, construct the category tables and determine the clustering center of each category. [1] In this paper, they look into the effectiveness of classification based approaches on image retrieval datasets. They evaluate on several standard retrieval datasets such as CAR-196, CUB-200-2011, Stanford Online Product, and In-Shop datasets for image retrieval and clustering, and establish that our classification-based approach is competitive across different feature dimensions and base feature networks. They further provide insights into the performance effects of sub-sampling classes for scalable classification-based training, and the effects of binarization, enabling efficient storage and computation for practical applications. [3] In this work author propose a new method for DML, featuring a joint learning of the embedding space and of the data distribution of the training categories, in a single training process. Their method improves upon leading algorithms for DML-based object classification. Furthermore, it opens the door for a new task in Computer Vision a few-shot object detection, since the proposed DML architecture can be naturally embedded as the classification head of any standard object detector. [4] In this work they show how to improve the robustness of such embeddings by exploiting the independence within ensembles. To this end, we divide the last embedding layer of a deep network into an embedding ensemble and formulate training this ensemble as an online gradient boosting problem. Each learner receives a reweighted training sample from the previous learners. Further, they propose two loss functions which increase the diversity in our ensemble. These loss functions can be applied either for weight initialization or during training. Together, their contributions leverage large embedding sizes more effectively by significantly reducing correlation of the embedding and consequently increase retrieval accuracy of the embedding. [5] In this work they identify two critical limitations of the sample mining methods, and provide solutions for both of them. First, previous mining methods assign one binary score to each sample, i.e., dropping or keeping it, so they only selects a subset of relevant samples in a mini-batch. Therefore, they propose a novel sample mining method, called Online Soft Mining (OSM), which assigns one continuous score to each sample to make use of all samples in the mini-batch. OSM learns extended manifolds that preserve useful intraclass variances by focusing on more similar positives. Second, the existing methods are easily influenced by outliers as they are generally included in the mined subset. To address this, they introduce Class-Aware Attention (CAA) that assigns little attention to abnormal data samples. Furthermore, by combining OSM and CAA, they propose a novel weighted contrastive loss to learn discriminative embeddings. [6] In this paper, they propose a deep adversarial metric learning (DAML) framework to generate synthetic hard negatives from the observed negative samples, which is widely applicable to supervised deep metric learning methods. Different from existing metric learning approaches which simply ignore numerous easy negatives, the proposed DAML exploits them to generate potential hard negatives adversarial to the learned metric as complements. They simultaneously train the hard negative generator and feature embedding in an adversarial manner, so that more precise distance metrics can be learned with adequate and targeted synthetic hard negatives. [8] In this study author hypothesize that there is an inherent mapping between frontal and profile faces, and consequently, their discrepancy in the deep representation space can be bridged by an equivariant mapping. To exploit this mapping, we formulate a novel Deep Residual EquivAriant Mapping (DREAM) block, which is capable of adaptively adding residuals to the input deep representation to transform a profile face representation to a canonical pose that simplifies recognition. The DREAM block consistently enhances the performance of profile face recognition for many strong deep networks, including ResNet models, without deliberately augmenting training data of profile faces.

IV PROBLEM IDENTIFICATION

Image Classification and retrieval is current research trend in computer vision. The application of image classification used in various field such as remote sensing, Photo Gallery and Medical diagnosis. In concern of classification, the rate of classification depends on the feature attributes of image data and depends on behavior of classifier. In process of survey study paper and journal of image classification based on various data mining approach and neural network. Some Classification based on binary classes and some other one are multilevel classification. The binary classification generate a issue for MSE(Mean Square Error) and degrade the rate of prediction in classification such as Decision Tree , Navie Bayes etc. In another approach multilevel classification generates large number of confusion matrix and suffered rate of classification. Now in my base paper used SVM classifier with DAG and improved accuracy and rate of classification, but it also suffered from multiple hyper plane class.

V CONCLUSION AND FUTURE SCOPE

In content based color image classification systems, images are usually represented by high-dimensional visual perceptive feature vectors, and the similarity between two images is defined by a distance function, e.g., Euclidean distance. Feature extraction is very important phase of image classification. The extraction of feature process in two different modes on is frequency domain and another is frequency domain. In this paper we review the various classification techniques of image processing.

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