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Paper Authors

CH.DURGABHAVANI, T.NAGARAJU,T.HARISH, P.PRASANTHI V.V.S SAIRAM,DR.P.CHENNARAO
Sri Sarathi Institute Of Engg &Technology.
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AN EFFECTIVE CONTENT BASED IMAGE RETRIEVAL BY USING CNN CLASSIFIER

[1]CH.DURGABHAVANI, [2]T.NAGARAJU, [3]T.HARISH, [4]P.PRASANTHI
[5]V.V.S SAIRAM
DR.P.CHENNARAO, PROFESSOR
Sri Sarathi Institute Of Engg &Technology
Mail id: haichenna@rediffmail.com

Abstract

An effective content-based image retrieval (CBIR) system depends on the discriminative feature which represents an image. In this work, we explore deep convolutional features for a CBIR system. We first show the effectiveness of deep convolutional channel features for a CBIR system. Then we introduce a Multi- Level Pooling method (MLP) to obtain object-aware features from convolutional layers and finally the features extracted from different layers are incorporated to a short representation vector. Through multiple experiments, we show that our approach can achieve state-of-art results on several benchmark retrieval datasets

Introduction

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools.

The first microcomputer-based image database retrieval system was developed at MIT, in the 1980s, by Banireddy Prasaad, Amar Gupta, Hoo-min Toong, and Stuart Madnick.

Search methods

Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc.

- Image meta search - search of images based on associated metadata such as keywords, text, etc.
- Content-based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the

use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features.

- List of CBIR Engines - list of engines which search for images based image visual content such as color, texture, shape/object, etc.

Data Scope

It is crucial to understand the scope and nature of image data in order to determine the complexity of image search system design. The design is also largely influenced by factors such as the diversity of user-base and expected user traffic for a search system. Along this dimension, search data can be classified into the following categories:

- Archives - usually contain large volumes of structured or semi-structured homogeneous data pertaining to specific topics.
- Domain-Specific Collection - this is a homogeneous collection providing access to controlled users with very specific objectives. Examples of such a collection are biomedical and satellite image databases.
- Enterprise Collection - a heterogeneous collection of images that is accessible to users within an organization's intranet. Pictures may be stored in many different locations.
- Personal Collection - usually consists of a largely homogeneous collection and is generally small in size, accessible primarily to its owner, and usually stored on a local storage media.

- Web - World Wide Web images are accessible to everyone with an Internet connection. These image collections are semi-structured, non-homogeneous and massive in volume, and are usually stored in large disk arrays.

CBIR attracts much attention both academically and commercially for decades. The retrieval performance of a content-based image retrieval system crucially depends on the feature representation and similarity measurement. In early CBIR systems, images are indexed by their visual content, which is represented by low-level information, including color features, texture features and shape features. Although a variety of techniques have been proposed, the well-known "semantic gap" issue laying between low-level image pixels captured by machines and high-level semantic concepts perceived by human is still one of the most challenging problems in current CBIR research. In last few years, there were many important advances in machine learning. One important breakthrough is known as the deep learning technique, which includes several different types of deep architectures composed of multiple linear and nonlinear transformations. Deep learning has led to state-of-art performance on various problems such as image classification object detection face recognition , etc.

Among different types of deep neural networks, convolutional neural networks have been most extensively studied. Convolutional neural network (CNN) is first introduced by in and improved in . However, due to the lack of training data and computing power in early days, it is extremely hard to train a large high-capacity convolutional neural network. Recently, with the rapid growth of data size and the increasing computing power of graphics processor unit, many researchers used convolutional neural network to achieve start-of-art results on various tasks performance of CNN features on retrieval task. For example, has extensively evaluated the performance of the deep features extracted from fully connected layers with and without fine-tuning on related dataset, and overall reported that the features from fc layers outperform traditional SIFT-like features. proposed a method called Convolutional Channel Features (CCF), which transfers low-level features from pre-trained CNN models to feed the boosting forest model. The work shows that convolutional channel features serve as a good way of tailing pre-trained CNN models to diverse tasks without fine-tuning the whole network to each task by achieving state-of-art performances in pedestrian detection, face detection, edge detection and object proposal We have shown that using locally normalized histogram of gradient orientations features similar to SIFT descriptors in a dense overlapping grid gives very good results for person detection, reducing false positive rates by more than an order of magnitude relative to the best Haar wavelet based detector from . We studied the influence of various descriptor parameters and concluded that fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all important for good performance. We also introduced a new and more challenging pedestrian database, which is publicly available.Convolutional neural network (CNN) is a type of feed-forward artificial neural network where the individual neurons are tiled in such a way that they respond to overlapping re-gions in the visual field" [11]. They are biologically-inspired invariant of Multilayer Per-ceptrons (MLP) which are designed for the purpose of minimal preprocessing. These mod-els are widely used in image and video recognition. When CNNs are used for image recog-nition, they look at small portions of the input image called receptive fields with the help of multiple layers of small neuron collections which the model contains [11]. The results we get from this collection are tiled in order for them to overlap such that a better represen-tation of the original image is obtained; every such layer repeats this process. This is the reason they are able if the input image is translated in any way. The outputs of neuron clus-ters are combined by local or global pooling layers which may be included in convolutional networks. Inspired by biological process, convolutional networks also contain various com-binations of fully connected layers and convolutional layers, with point-wise nonlinearity applied at the end of or after each layer [11]. The

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convolution operation is used on small regions so as to avoid the situation when if all the layers are fully connected billions of pa-rameters will exist. Convolutional networks use shared weights in the convolutional layers i.e. for each pixel in the layer same filter (weights bank) is used which is advantageous because it reduces the required memory size and improves performance. CNNs use rela-tively less amount of pre-processing as compared to other image classification algorithms, meaning that the network learns the filters on its own which are traditionally manually-engineered in other algorithms. CNNs have a major advantage over others due to the lack of a dependence on prior-knowledge and the difficult to design hand-engineered features.

4.1.1 Sparse Connectivity

CNNs enforce a local connectivity pattern between neurons of adjacent layers to exploit spatially-local correlation [6]. We have illustrated in fig.4.1 that in layer m the inputs of hidden units are from a subset of units in layer m-1, units containing spatially adjoining receptive fields.

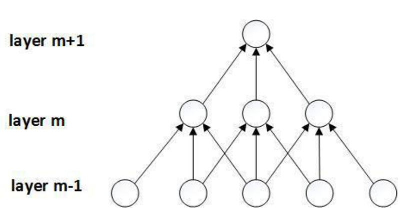

Figure 4.1: Sparse Connectivity [6]

Let us consider layer m-1 as an input retina. It can be seen in the figure that the layer m have receptive fields of width 3 in the input retina and are thus connected only to 3 adjacent neurons in the retina layer [6]. There is similar connectivity between the units in layer m+1 and the layer below. It can be said that their with respect to the input receptive field is larger where as with respect to the layer below their receptive field is 3. There is no response in the each unit to variations which are outside their receptive fields with respect to the retina thus ensuring that the strongest response to a spatially local input pattern is produced by the learnt filter

4.1.2 Shared Weights

Every filter h_i in CNNs is duplicated across the complete visual field. The duplicated filters consists of the same parameters i.e. weights and bias that form a feature map. We can see in fig.4.2 that same feature map contains 3 hidden units. The weights of same color are shared that are constrained to be identical [6]. We can still use gradient descent to learn such shared parameters by altering the original algorithm by a very small margin. When the gradients of the shared parameters are summed, then it gives the gradient of a shared weight. We can detect the features regardless of their location in the visual field by duplicating the units. The huge reduction of the number of free parameters being learnt can lead to weight sharing increasing the learning efficiency. CNNs achieve better generalization on vision problems due to the constraints on these models.

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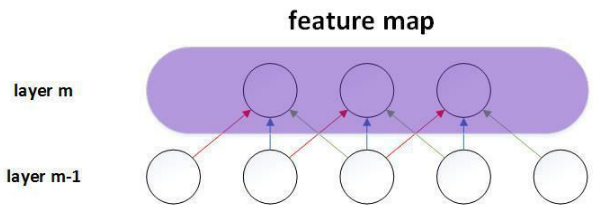

Figure 4.2: Shared Weights [6]

4.4 System Design

The fig.4.6 illustrates how the system of retrieval works for this study. The query image is pre-processed and is evaluated with the trained neural network and the regions are clas-sified. It is then matched against the annotation index with images on which the neural network was trained. All the images in the dataset which are similar to the query image are returned to the user based on the number of images required by him. In other words, top N images similar to the query image are retrieved. This section briefly explains the major components of the system design:

Query ImageThe query image is a user input image which he wants to use as a sample to retrieve images from the dataset. The query image can be from any source and need not be from our dataset. An example of query image can be seen in The image has to be pre-processed before it is evaluated by the trained neural network because the dataset on which the network was trained had images pre-processed and works with specific constraints. The image is converted to grayscale and is resized to 28x28 pixels as a part of pre-processing step. Once the query image is a 28x28 pixel grayscale image it can be evaluated with the train model.

Trained Neural Network

I have discussed in section 4.3 how I trained the neural network. The result that is returned after training is a train model which is a Theano function. After the query image is con-verted to grayscale and is resized it is evaluated with the train model. Based on the training results the regions of the query image are classified according to the class labels. This information is stored and is used for matching against the annotation index.

Annotation Index

I built an annotation index with the help of the annotations provided with every image. The index contains the regions that have been annotated and classified by the users for each image. I check for labels from valid regions to get new labels. These labels are added to the index and for each label only once an image is added to the index. This results in an index which contains the information about all the labels present in each image. The annotation index is also used for generating a mapping for labels based on the existing active labels. I maintain a synonym list which contains the synonyms for all the 8 classes that I am using. These synonyms are names used by users to annotate the images. For example in some cases sky is annotated as cloudy sky, clear sky, sky etc. To handle this situation mapping is done for the labels to be mapped to their synonyms. Once the annotation index is ready the dataset is compressed using the annotation index, images and the mapping.

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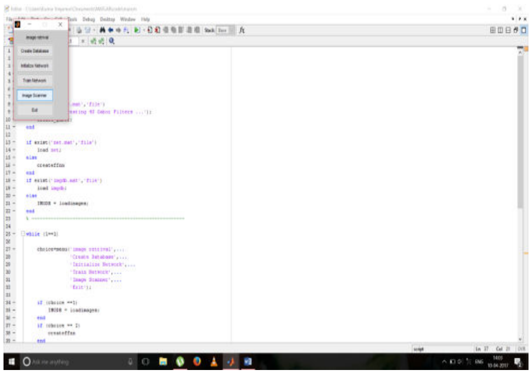
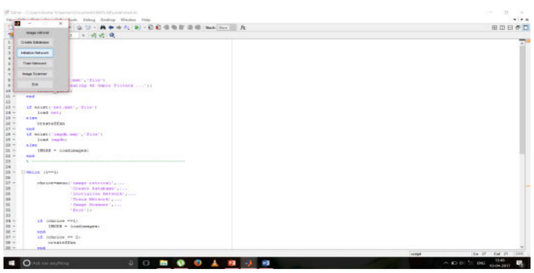
Create data base



Intalize network



Train data

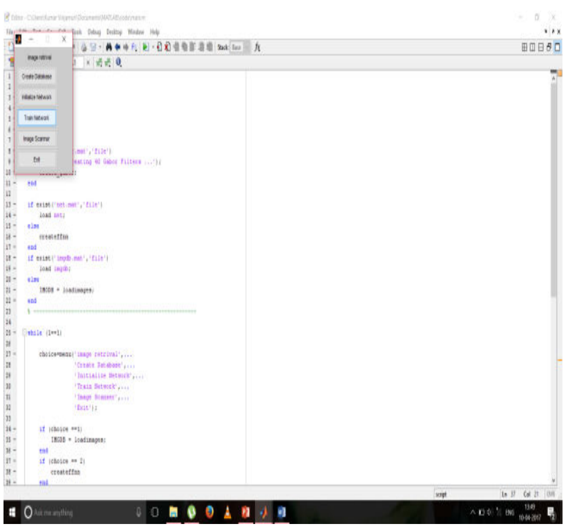
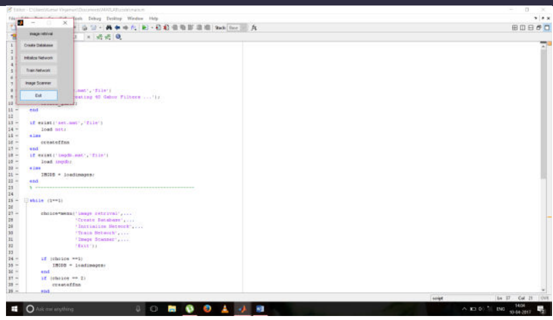


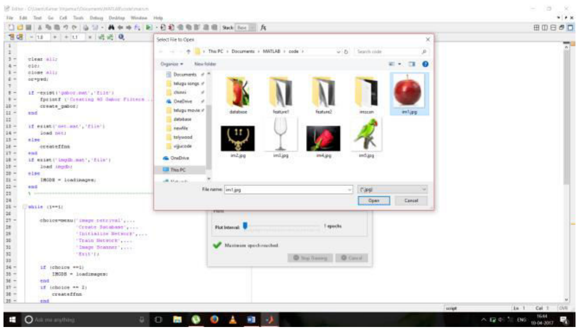
Image scanner

Exit

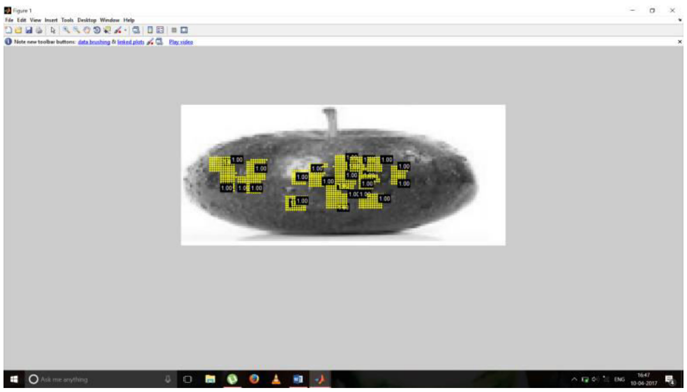


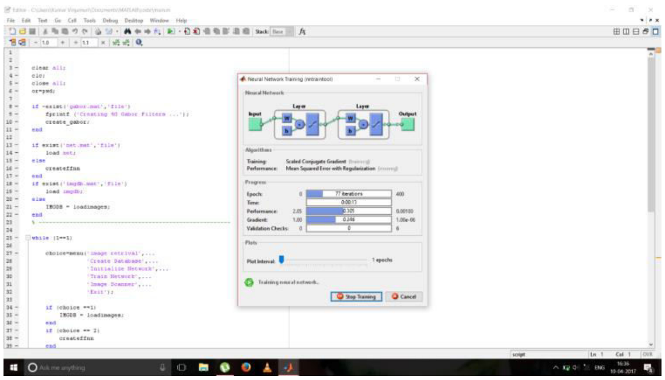
cnn layer

Selection of Input image



Weights of input image





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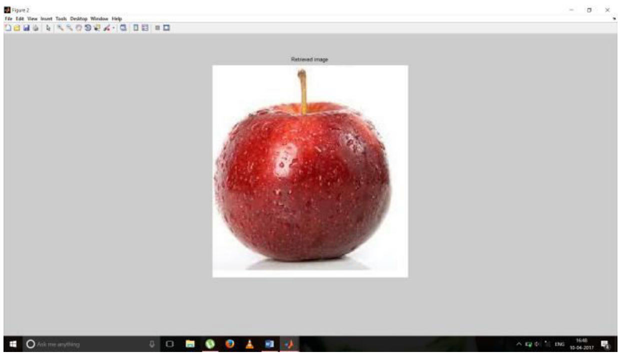
Output or retrival image



Conclusion

In this work, we evaluate the performances of different layers in deep CNNs for content-based image retrieval system, and propose a multi-level pooling method to obtain object-aware representation. We aggregate features from the low-level and high-level layers to form our final representation, which contains both vision and semantic information. We achieve state-of-art results on several benchmark retrieval datasets and a large-scale practical commodity dataset with the statical parameters compress operation on the final representation.

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