Recognition of OPS using Google Street View Images

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Abstract - *The various application scenarios give rise to a key technique of daily life visual object recognition. On-premise signs (OPSs), a popular form of profitable advertising, are mostly used in our daily life. The OPSs often demonstrate great visual variety, accompanied with complex ecological conditions. In this paper we have used the OPS-62 dataset. The OPS-62 dataset contains 4649 OPS images of 62 different categories. We used Speed Up Robust Features algorithm to extract feature like background, foreground, size etc. from OPS-62 images. We have used distributional clustering for variable clustering. Further, for addressing the problem of real-world OPS learning and recognition, we developed a probabilistic framework based on the distributional clustering, in which we proposed to exploit the distributional information of each visual feature (the distribution of its associated OPS labels) as a reliable selection criterion for building discriminative OPS models.*

Key Words: Real-world objects, street view scenes, learning, recognition, object image data set.

1. INTRODUCTION

It is an easy way while interacting with the network we can use the image based mobile applications for example, an user traversing through a road want to visit a shop , so on the basis of surrounding images of that shop ,it may including various hoardings , logos, path names etc. user get the proper address of that shop. When these various attributes are used for recognition of that images. As image is recognized the user know whole details about that shop and services provided by them. In approach the learning phase consists no pixel wise object labeling even the recognition scheme is simple, linear, and Can be executed in parallel fashion from a communication system perception. For the generation codebook object category a visual saliency base procedure is used to reduce noise visual words. Distributional clustering is used to extracts discriminative visual words of OPS to recognize and localize OPS images that measure the sharpness of code words for each object category.

For communication system we developed real word object recognition system. This system not required pixel wise images in the learning phase for identify the recognition scheme. This scheme is executed in parallel fashion. For generating the codebook of object categories, visual saliency based procedure is used to reduce noisy visual words. Distributional clustering to measure the discriminative ness of code words with respect to each object category. This system is beneficial for to create the new benchmark for object recognition of OPS-62.

Instead of generating strong labels for real-scene images, an alternative learning technique, this is weakly supervised by a dataset with each image labeled with the OPS category it contains, i.e., a weakly labeled image. To create a recognizable image for a business to attract customers, each business has its own OPSs which is a visually consistent image for a brand and contains a mixture of text and graphics Conroy et al[7]. Therefore here, proposed a probabilistic framework for learning and recognition of OPSs in real-world images. Real-world characteristics of OPSs, such as viewing angles, arbitrary size, occlusions, varying lighting conditions, foreground and background clutter, etc., make logos, texts, or trademarks in OPSs fill a smaller area by other objects in real scene images. All these characteristics fail to identify texts or logos in OPSs of existing solutions. The main approach is to take advantage of probabilistic framework to extract discriminative visual words of each OPS category and therefore able to localize and recognize each OPS within images by using learnt OPS model. The intimate presence of mobile devices in our daily life has dramatically changed the way we connect with the world around us.

Users rely on mobile devices to maintain an always-on relation to information and personal networks Girod et al[4]and thereby can access in-situ information Manuscript received December 19, 2012; revised June 21, 2013 and October 6, 2013; accepted December 12, 2013. Date of publication January 9, 2014; date of current version January 23, 2014.

This work was supported in part by the National Science Council under Grant NSC-102-2221-E-001-028 and in part by the Industrial Technology Research Institute. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Andrea Cavallaro related to nearby everyday objects or stores by using image based mobile interactions through their devices. For example, as users walk on the street, they might simply point the mobile camera to a store on the street to quickly access its related information, inquire special offers, and make reservations through their mobile devices without physically entering the store.

2. SYSTEM ARCHITECTURE

In this system, user gives input as image which is captured through mobile cameras. System gives input images and perform the actual proposed framework on given input image. In this framework two basic algorithms are used: first is visual saliency based codebook generation of OPS categories. In this algorithm first, filter out the background region for minimizing the number of noisy visual word using visual saliency analysis. After removing the background noise, visual feature are extracted using dense sampling strategy and Opponent SIFT descriptor for codebook Generation. After acquiring a codebook for each OPS category compute a discriminative subset and apply a distributional clustering to collecting of all the code words in OPS categories into two disjoint clusters. Then allow the concurrent OPS recognition and localization in super-pixel level using obtained OPS and background models. Second algorithm is OPS modelling and recognition using distributional Clustering here, super pixel segmentation performed on input image.

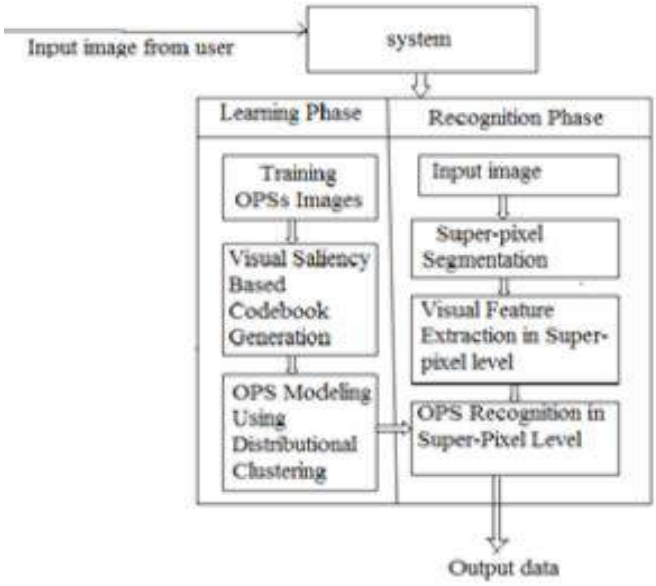

Fig. 2.2.1: System Architecture

After the segmentation visual feature extraction in super pixel level then recognized the OPS image with learned dataset.

We now describe the reranking of the returned images based on text and metadata alone. Here, we follow and extend the method proposed by Fergus et al[9] in using a set of textual attributes whose presence is a strong indication of the image content.

3. SYSTEM ANALYSIS

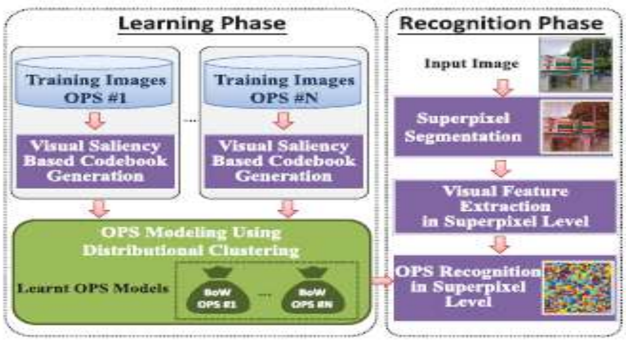

Fig. 3.1 Overview of the proposed system framework.

3.1 Module Description

After careful analysis the system has been identified to have the following modules:

a. On-Premise Signs
b. Image Data Set
c. Recognition
d. Learning

a. On-Premise Signs

These are signs that are located on the same premises on which the activity is conducted. Any property, on which a sign is placed, that is not integral to the activity, or is separated from the activity by a roadway, highway, common driveway, or other obstruction, or is at such distance that the sign is closer to the highway than the activity is not considered on-premises. Also, if the sign is located on a narrow strip of land whose only real purpose is to accommodate the sign, and is not used for the advertised activity, the sign cannot be considered on-premises. These rules apply regardless of whether the properties are under the same ownership. On-premises signs in the controlled area may be subject to registration in accordance with Section 86 of the Highway Law.

b. Image Data Set

Instead of generating strong labels for real-scene images, we resort to an alternative learning technique, which is weakly supervised by a dataset with each image labeled with the OPS category it contains, i.e., our, learning involves a significant amount of human labor, and thereby is usually not feasible for training a real-scene OPS model. Instead of generating strong labels for real-scene images, we resort to an alternative learning technique, which is weakly supervised by a dataset with each image labeled with the OPS category it contains, i.e., a weakly labeled image , learning involves a significant amount of human labor, and thereby is usually not feasible for training a real-scene OPS model. Instead of generating strong labels for real-scene images, we resort to an alternative learning technique, which is weakly supervised by a dataset with each image labeled with the OPS category it contains, i.e., a weakly labeled image

c. Recognition

The task of recognizing and localizing OPSs in real-world scenes can be viewed as a problem of real-world visual object recognition consistent image for a brand and contains a mixture of text (e.g. the business's name) and graphics (e.g. corporate trademarks/logos). Nature of digital information has become increasing visual, and so has the need for companies to locate and identify in the digital ocean. Explore what the industry leader in image recognition technology has to say about making sense of visual content in this digital world. Table 3.1.1 details the statistics for each of the three retrieval techniques (Web Search, Image Search, and Google Images). Note that some images are common between the methods. Image Search a very low precision (only about 4 percent) and is not used for the harvesting experiments. This low precision is probably due to the fact that Google selects many images from Web gallery pages which contain images of all sorts. Google is able to select the in-class images from those pages, e.g., the ones with the object-class in the filename; however, if we use those Webpages as seeds, the overall precision greatly decreases.

Service	in-class	non-class	precision
WebSearch	8773	25252	26%
ImageSearch	5963	135432	4%
GoogleImages	4416	6766	39%

Table 3.1.1: Statistics by Source: The Statistics of Downloaded Images

4. CONCLUSIONS

A probabilistic framework for learning and recognizing real-world OPSs from weakly labeled street view images, in which the technique of distributional clustering is exploited to benefit the selection of discriminative visual words and the construction of effective OPS models, as motivated by the communication theory. Meanwhile, we proposed the OPS-62 image dataset which contains more real world characteristics as a new benchmark for visual object recognition. In comparison to the state-of-the-art pLSA models, our approach can improve the average OPS recognition rates from 0.273 to 0.686, with a significant 151.28% relative improvement. However, in view of the low average recall values relatively, the OPS recognition in real-world scenes is still a challenging problem.

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