Efficient Geo-tagging of images using LASOM

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Abstract -*Automated identification of the geographical coordinates based on image content is of particular importance to data mining systems, because geo-location provides a large source of context for other useful features of an image. In this paper we propose an on-line, unsupervised, clustering algorithm called Location Aware Self-Organizing Map (LASOM), for learning the similarity graph between different regions. The goal of LASOM is to select key features in specific locations so as to increase the accuracy in geo-tagging untagged images, while also reducing computational and storage requirements. We demonstrate that the generated output not only preserves important visual information, but provides additional context in the form of visual similarity relationships between different geographical areas. We further show that the learned representation results in minimal information loss as compared to using k-Nearest Neighbor method. The noise reduction property of LASOM allows for superior performance when combining multiple features.*

Key Words: **Geo-tagging, Geo-location, Self Organizing Map, Clustering, k-Nearest Neighbor.**

1. INTRODUCTION

We live in an information age touched by technology in all aspects of our existence, be it work, entertainment, travel, or communication. The extent to which information pervades our lives today is evident in the growing size of personal and community footprints on the web, ever improving modes of communication, and fast evolving internet communities (such as Flickr, Twitter, and Facebook) promoting virtual interactions. In some aspects, man has transformed from a social being into an e-social being. Images and video constitute a huge proportion of the Web information that is being added or exchanged every second. The popularity of digital cameras and camera phones has contributed to this explosion of personal and Web multimedia data.

The geographical origin of an image is important contextual information that can help in many applications, including but not limited to tourism recommendation and landmark identification. It can also provide important semantic information for articles, while surveillance systems could use geo-tags to locate missing people. Knowledge about geographical regions can also inform about the objects and buildings that should be expected in the image or in the case of densely populated areas, whether people detection algorithms should be used. Therefore, it is desirable to augment any image that might lack geographical location (e.g. GPS coordinates) with our estimate of where the image was taken. Geo-tagging of images however, is a very difficult task due to the variability of visual data across the globe. Taking two photographs at the same location, but at different angles, may yield two images with vastly different pixel values. Modeling such data is not an easy task. To capture this variability, a large dataset is required.

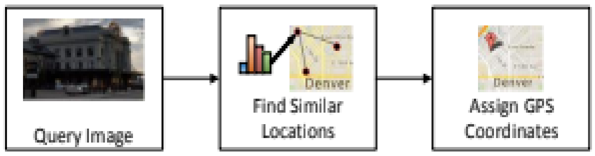

Fig-1: Process Flow

Understanding where user generated images come from (e.g. Beijing or New York) can be a great source of contextual information. For example, object detection can be constrained to search for location-specific objects. The number of photos taken at a location can provide information about the popularity of a particular place, which can be used in tourist recommendation systems. Image search and retrieval can also benefit greatly from this work. Finding videos and images related to a particular location or even places mentioned in a news story is of great interest to mass media. Images and videos recorded in the same area tend to be related in terms of activity and content.

Finally, determining where an image was taken is valuable to the intelligence community for use in surveillance. The availability of geo-tagged images on sites such as Flickr has allowed researchers to explore the problem of automatic geo-tagging of images and videos that are missing such information. Most successful approaches have combined media tags with global image descriptors and authorship information. Yet, there is plenty of untapped information that still exists in image content. Understanding how features are distributed in the world and using such information can improve geo-tagging performance. Specifically, this information can be used for building a list of geographical regions where a query might have originated. Many geo-location techniques will first perform some form of clustering before training a classifier to clusters detect which cluster a query image belongs to. These are either done on the location information or on the visual features, using such methods as k-means or mean shift. In this paper we propose a new on-line unsupervised clustering algorithm, called Location Aware Self-Organizing Map

(LASOM) that can be used for estimating the density distribution of one variable conditioned on another. LASOM is able to compress the large amounts of data by not storing commonly occurring images and by storing only the features that are required for discriminating one geographical region from another. It removes noise by removing features that occur very rarely and it gives us the ability to discover the similarities and differences between different regions.

1.1 Goals and Objectives

- Geo-tagging allows user to visualize and manage photo collection in many ways.
- Using a collection of over a million geo-tagged pictures, we build location.
- Probability maps for commonly used images tags over the entire globe.
- It is easy to find out location, where the photo is taken.

2. LITERATURE SURVEY

The Self-Organizing Map (SOM) algorithm [1] is a well-known method, which provides both data reduction and projection in an integrated framework. Using regular 2D grids as neural structures for the SOM training ,visualization form of the maps, component planes, and distance distributions comprise basic methods visual for exploration of data using SOM processing [2]. SOM-based Visual Analysis to date has considered different application domains, including financial data analysis based on multivariate data models [3], analysis of web click stream data using Markov Chain models [4], trajectory oriented data [5], or time-oriented data [6].Image Sorter [7] proposed to visually analyze collections of images by training a SOM over color features extracted from the images. We here follow that idea, in that we analyze geo-spatial heat maps of sentiment scores using SOM of respective color features as well. When considering geo-referenced data with SOM, basically two approaches exist. First, in the joint data model, one single data representation is formed by combining spatial and other multivariate data into a single vector representation which is input to the SOM method. Examples include [10], where a joint vector representation for both geo-location and demo graphic data was formed for census data analysis. More methods can be found in [11].

3. EXISTING SYSTEM

In the earliest system the problem was to identify the actual location of an image means they were not provide the accurate result of location only produced the predicted result. Content understanding in images has been studied for decades in the vision research community.Recently, the research community increasingly turns to metadata and picture taking context solve the semantic understanding problem. Important metadata can be collected also as a result of user participation.

Photo sharing websites such as Flickr have witnessed as urge of collaborative tagging from users. When an image is manually tagged, the user associates annotations with the image that are descriptive and may carry information related to the location of the image. In some cases, the relationship is direct: An image tagged "Chicago" is quite probably captured in the Illinois city. However, in other cases the relationship is more subtle but still informative. For example, an image tagged "snow" is not likely to have been captured near the equator. Other tags, such as "smile", contain little information regarding the locationof the image capture. The benefit of user tags is clear from Fig. 1. Even if you think you know the location of an image from the content, the tags collectively can provide valuable information. If we jumped to the conclusion that this statue is in NYC, we would be drawing a reasonable but incorrect conclusion. While location has been used for image understanding; the inverse problem of inferring location from image content is still novel and difficult.

4. IMPLEMENTED SYSTEM

In this paper the user will provide the images for finding the location in the maps. The Geo-tagging phenomenon used here the images in a particular location in the maps. More specifically we want to find arg max. Calculating this directly is very difficult, due to the large variability of visual data at each possible location. We discuss the details of a new on-line, unsupervised clustering algorithm that compresses large databases by only keeping the information required to identify a specific location. Location Aware Self-Organizing Map LASOM is a specialized algorithm for learning the distribution of one feature conditioned on another one. Spatial constraints will be used to learn the distribution of visual features at particular geographical locations. To evaluate LASOM dataset and features. The spatial distribution of images, while the training set is noisy and contains a number of distant training samples(Best viewed zoomed in and in color).Intuitively, this process can be seen as moving a codebook vector in feature space until the center (i.e. average) of that space is found. This movement is constrained by neighboring nodes. In this entire process can be seen as spatial binning of visual information, where the bin centers do not have to be determined a-priori, and are based on the visual variability in a particular region (i.e. more codebooks are dedicated to highly variable areas).Querying LASOM in this process assign a location to an untagged image. The code vector represents a region in feature space. To provide better estimates, the query feature is once again compared to code vector and all its immediate neighboring nodes and the weight are normalized for calculating the location. Experiments showed that using an exponential with a base of resulted in superior performance.

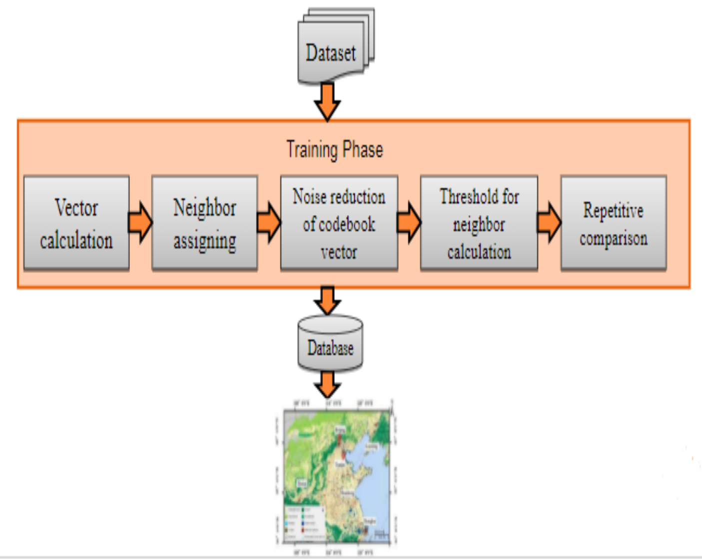

Fig-2: System Architecture

4. FUTURE SCOPE

Other applications consolidate large scale dataset of geo-tagged information to produce map that indicate where things are in the world taken as image. We expect future geo-tagging driven research and applications to develop in several directions, including dealing with large scale data, fusion of multi-modality information.

5. CONCLUSIONS

We have proposed geo-tagging in large no. of data with the use of LASOM. The goal of LASOM is to select key features in specific locations so as to increase the accuracy in geo-tagging untagged images, while also reducing computational and storage requirements. We demonstrate that the generated map not only preserves important visual information, but provides additional context in the form of visual similarity relationships between different geographical areas. We show how this information can be used to improve geo-tagging results when using large databases. We further show that the learned representation results in minimal Information loss as compared to using k Nearest Neighbor method. The noise reduction property of LASOM allows for superior performance when combining multiple features.

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