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Location Recognition Using Nearest Neighbour Feature Matching

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Abstract: ***There are many computer vision problems, the most time consuming component consists nearest neighbor matching in high-dimensional spaces. There are no known exact algorithms to solve these types of high-dimensional problems that are faster than linear search. Approximate algorithms provide large speedups with only minor loss in accuracy, but many such algorithms have been published with only minimal guidance on selecting an algorithm and its parameters for any given problem. In this paper, we describe a system that answers the question, "What is the fastest approximate nearest-neighbor algorithm for my data?" Our system will take any given dataset and desired degree of precision and use these to automatically determine the best algorithm and parameter values. We also describe a new algorithm that applies priority search on hierarchical k-means trees, which we have found to provide the best known performance on many datasets. After testing a range of alternatives, we have found that multiple randomized k-d trees provide the best performance for other datasets. We are releasing public domain code that implements these approaches. This library provides about one order of magnitude improvement in query time over the best previously available software and provides fully automated parameter selection.***

Keywords: ***Neighbor Matching, Generalized Graphs, GMCP-Tracker, k-means tree algorithm***

1.INTRODUCTION

Recently, many large scale image geo-localization methods which employed techniques that are similar to image matching have attracted much interest. In these methods, a reference data set consisting of geo tagged images is available. Then, the problem is to estimate the geo-location of a query image by finding its nearest neighbor from the given reference images. Hays and Efros developed a simple method for extracting the geographical information from a query image using a data set of Flicker images. We proposed a framework which utilized Google Street View images as the reference data set; it is a feature pruning method which incorporates geospatial information, it was employed to discover incorrectly matched features. Sattler developed a new framework which is similar in identifying 2D-to-3D correspondences between the query and the reference data set. In [1], they presented an efficient method for the same purpose based on 2D-to-3D and 3D-to-2D matching. Mostly these methods utilize only local features which ignore the global context of the image. In addition, number of approaches has been developed to deal with the repetitive visual patterns in the data sets. Such patterns, e.g., recurrent architectural structures, exacerbate the susceptibility of local features to mismatches caused by ignoring the global context.

In this paper, we propose an approach for image geo-localization, it finds one or few strongly matching reference images to a query by discovering local feature correspondences. Here to address the weakness of local features in leveraging the global context, our method considers multiple references nearest neighbors (NN) as the potential matches for each query image and selects the correct ones by examining the consistency among their global features. We performed our experiments using different types of global features, such as GIST, color histogram, and image geo-tag; all these are shown to improve the performance while the geo-tags yielded the best overall results.

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We use the Generalized Minimum Clique Problem (GMCP) at the core of our feature matching method. GMCP is useful where there are multiple potential solutions for a number of subproblems, as well as a global criterion among the subproblems to be satisfied. In our framework, each subproblem is matching a query feature to the reference features, the potential solutions are the NNs, and the global criterion is the consistency of global features of the NNs. Therefore, we utilize GMCP in performing our multiple nearest neighbor features matching, and a voting scheme on the matched features is employed to identify the strongly matching reference image(s) and estimate the geo-location. Therefore, the space in which local and global features are matched are kept separate, and different metrics can be used for each. Our method matches all the features of one image simultaneously which essentially means they contribute to each others match. This is different from the existing methods which perform feature matching on an individual basis. The main contributions of this paper can be summarized as 1.A multiple nearest neighbor feature matching method based on Generalized Minimum Clique Graphs. 2. A novel framework for incorporating both local and global features in image geo-localization. 3. A new data set of high resolution street view images.

2.PREVIOUS RESEARCH

The kd-tree algorithm is most widely used for nearest-neighbor search which works well for exact nearest neighbor search in low dimensional data, but quickly loses its effectiveness as dimensionality increases. Arya modified the original kd-tree algorithm to use it for approximate matching. They impose a bound on the accuracy of a solution using the notion of *approximate* nearest neighbor. The authors also propose the use of a priority queue to speed up the search in a tree by visiting tree nodes in order of their distance from the query point. Beis and Lowe (Beis and Lowe, 1997) describe a similar kd-tree based algorithm, but use a stopping criterion based on examining a fixed number *Emax* of leaf nodes, which can give better performance than the e-approximate cutoff. Silpa-Anan and Hartley (Silpa-Anan and Hartley, 2008) propose the use of multiple randomized kdtrees as a means to speed up approximate nearest neighbor search. They perform only limited tests, but we have found this to work well over a wide range of problems. Liu et al. (Liu et al., 2004) propose a new kind of metric tree that allows an overlap between the children of each node, called the spill-tree. However, our experiments so far have found that randomized kdtrees provide higher performance while requiring less memory. Nister and Stewenius (Nister and Stewenius, 2006) present a fast method for nearest-neighbor feature search in very large databases. Their method is based on accessing a single leaf node of a hierarchical k-means tree similar to that proposed by Fukunaga and Narendra (Fukunaga and Narendra, 1975). In (Leibe et al., 2006) the authors propose an efficient method for clustering and matching features in large datasets. They compare several clustering methods: k-means clustering, agglomerative clustering, and a combined partitional-agglomerative algorithm. Similarly, (Mikolajczyk and Matas, 2007) evaluates the nearest neighbor matching performance for several tree structures, including the kd-tree, the hierarchical k-means tree, and the agglomerative tree. We have used these experiments to guide our choice of algorithms.

The basic block diagram of the proposed image geo-localization method is shown below.

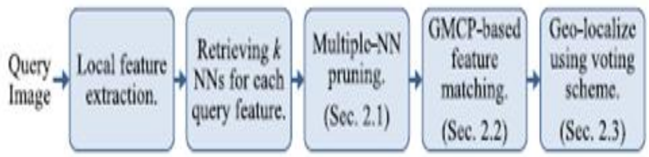

Fig.1. Image geo-localization method.

3.GENERALIZED MINIMUM CLIQUE PROBLEM:

Generalized Graphs, are also known as Generalized Network Design Problems , are a category of graph theory problems which are based on generalizing the standard subgraph problems. The generalization is

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done by extending the definition of a node to a cluster of nodes. For example, in the standard Traveling Salesman Problem (TSP) the objective is to find the minimal cycle which visits all the nodes exactly once. In the Generalized Traveling Salesman Problem, the nodes of the input graph are grouped into disjoint clusters; the objective is to find the minimal cycle which connects all the clusters while exactly one node from each is visited. Similarly, in the Generalized Minimum Clique Problem the vertices of the input graph are grouped into disjoint clusters. As shown in Fig. 2, the objective is to find a subset of the nodes that includes exactly one node from each cluster while the cost of the complete graph that the subset forms is minimized. A similar formulation is used to solve the Frequency Assignment Problem in telecommunications. It has been utilized for maximizing the number of comparisons between human detections in different video frames in order to perform data association as well.

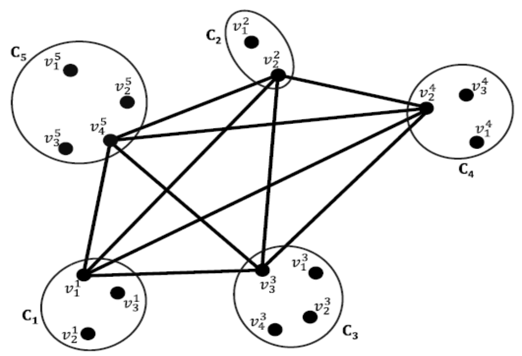

Fig2:An example GMCP. A feasible solution is shown where one node from each cluster is selected. The complete subgraph, Gs, which the selected nodes form is shown using the edges.

Our GMCP-based method differs from basic graphical models in various aspects. Our input graph and feasible solutions are complete as we consider the relationships among all possible pairs of local features. This makes our formulation different from the other graphical models which have specific assumptions on the structure of the graph, e.g., being acyclic.

4.GMCP-Tracker

The block diagram of the proposed global data association algorithm is shown in Fig. 3. The first step is to detect the humans in each frame. We used Felzenszwalb et al.'s [2] part-based human detector. Next, we divide the input video into a number of segments and find the tracklet of pedestrians within each segment using the proposed global method for tracklet generation utilizing GMCP. In the last step, we merge the tracklets found in all of the segments to form the trajectory of each person over the course of the whole video. Despite the appearance of the pedestrians remaining rather consistent throughout a video, the pattern of motion tends to differ significantly in short and long term. In principle, it's difficult to model the motion of one person for a long duration without having the knowledge of the destination, structure of the scene, interactions between people, etc. However, the motion can be modeled sufficiently using constant velocity or acceleration models over a short period of time. Therefore, the way motion is incorporated into the global data association process should be different in short and long terms. This motivated us to employ the hierarchical approach, i.e. finding tracklets first and then merging them into full trajectories.

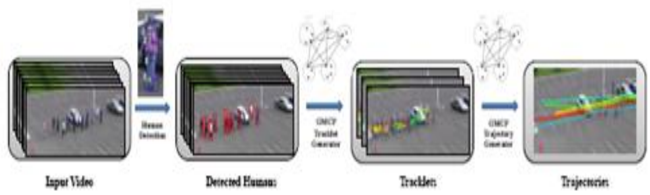

Fig.3 . The block diagram of the proposed human tracking method

5.FINDING FAST APPROXIMATE NEAREST NEIGHBORS

We have compared many different algorithms for approximate nearest neighbor search on datasets with a wide range of dimensionality. The accuracy of the approximation is measured in terms of precision, which is defined as the percentage of query points for which the correct nearest neighbor is found. In our experiments, one of two algorithms obtained the best performance, depending on the dataset and desired

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precision. These algorithms used either the hierarchical k-means tree or multiple randomized kd-trees. In this section, we will begin by describing these algorithms.

5.1.The hierarchical k-means tree algorithm

The hierarchical k-means tree is constructed by splitting the data points at each level into K distinct regions using a k-means clustering, and then applying the same method recursively to the points in each region. We stop the recursion when the number of points in a region is smaller than K. Figure1 shows projections of several hierarchical k-means trees constructed from 100K SIFT features using different branching factors.

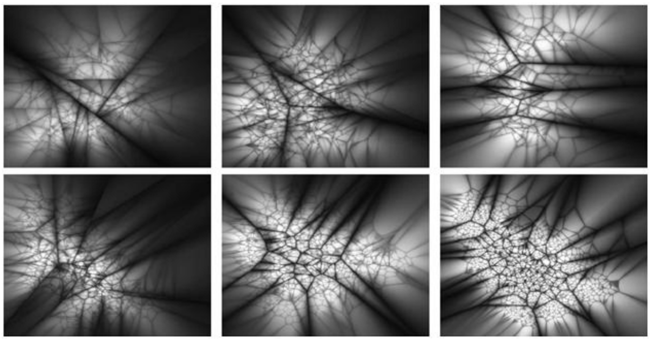

Fig.4. projections of several hierarchical k-means trees

We have developed an algorithm that explores the hierarchical k-means tree in a best-bin-first manner, exploration of the kd-tree. The algorithm initially performs a single traversal through the tree and adds to a priority queue all unexplored branches in each node along the path. Next, it extracts from the priority queue the branch that has the closest center to the query point and it restarts the tree traversal from that branch. In each traversal the algorithm keeps adding to the priority queue the unexplored branches along the path. The degree of approximation is specified in the same way as for the randomized kd-trees, by stopping the search early after a predetermined number of leaf nodes (dataset points) have been examined. However, these were found not to give improved performance.

5.2.The randomized kd-tree algorithm

The classical kd-tree algorithm (Freidman et al.,1977) is efficient in low dimensions, but in high dimensions the performance rapidly degrades. To obtain a speedup over linear search it becomes necessary to settle for an approximate nearest-neighbor. This improves the search speed at the cost of the algorithm not always returning the exact nearest neighbors. Silpa-Anan and Hartley (Silpa-Anan and Hartley, 2008) have recently proposed an improved version of the kd-tree algorithm in which multiple randomized kd-trees are created. The original kd-tree algorithm splits the data in half at each level of the tree on the dimension for which the data exhibits the greatest variance. We use the fixed value D = 5 in our implementation, as this performs well across all our datasets and does not benefit significantly from further tuning. When searching the trees, a single priority queue is maintained across all the randomized trees so that search can be ordered by increasing distance to each bin boundary. The degree of approximation is determined by examining a fixed number of leaf nodes, at which point the search is terminated and the best candidates returned. In our implementation the user specifies only the desired search precision, which is used during training to select the number of leaf nodes that will be examined in order to achieve this precision.

6. Merging Tracklets into Trajectories Using GMCP

We divide the video into S segments and find the tracklets of all the pedestrians in each segment using the data association method. In order to generate a trajectory of a person over the course of the full video, we need to merge the tracklets belonging to each person. This is a data association problem for which we can use any available data association method, such as bipartite matching [3,4]. However, in order to have a fully global framework, we use the same GMCP-based data association method we used for finding tracklets to merge them.

Therefore, the clusters and nodes in G now represent segments and tracklets, respectively (vs. representing frames and human detections). The appearance feature of a node, which represents one tracklet, is defined as the average appearance of the human detections in the tracklet (the mean of their color histograms), and its

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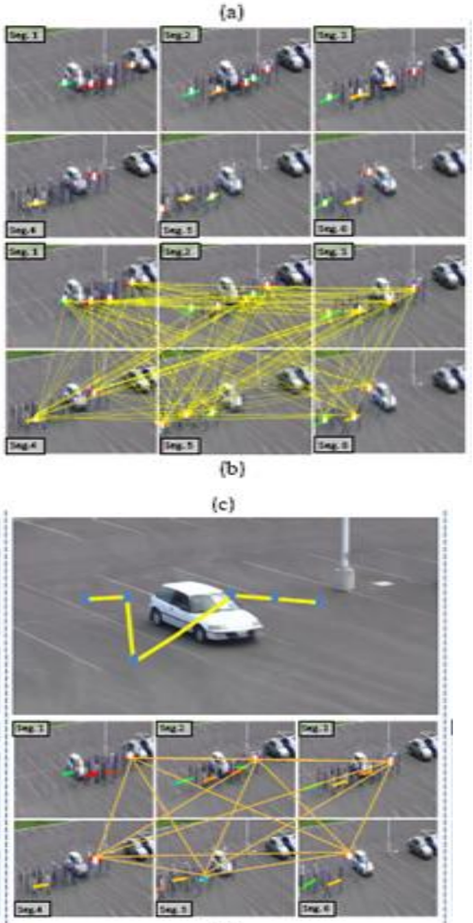
spatial location, x_im, is defined as the spatial location of the middle point of the tracklet. Fig. 5 (a) shows six consecutive segments with their tracklets, along with the complete graph their representative nodes induce in (b). Only four tracklets out of fifteen are shown to avoid cluttering of the plots.



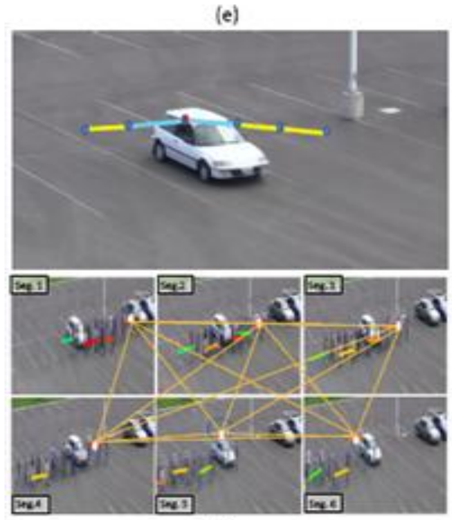


Fig. 5. Merging tracklets into trajectories.

7.SOLVING GMCP

GMCP is an NP-hard problem [5]. A few approaches for solving GMCP such as branch-and-cut and multi-greedy heuristics [6], [5] have been explored to date; however, the majority of them is formulated according to particular problems and are suited for small inputs [5]. Our graphs typically include L * k= 300 to 1; 500 nodes which require an efficient and approximate solver as the problem is NP-hard. Therefore, we employ Local-neighborhood Search to solve the optimization problem to work efficiently for large combinatorial problems such as Tabu-search for GMST [8], [9]. Local-neighborhood search methods are based on examining the neighbors of the current solution in hope of discovering a better one. Two solutions are neighbors of size ε if they are identical except in ε elements. Choosing a small neighborhood size makes the optimization process prone to getting stuck at suboptimal regions. On the other hand, choosing a large neighborhood significantly enlarges the number of neighbors in the each iteration, resulting in an increase in the complexity. In order to deal with these issues, we use a different approach in which we change the neighborhood size from repeatedly in each iteration.

8. EXPERIMENTAL RESULTS

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We evaluated the proposed algorithm using a reference data set of over 102,000 Google Street View images. The place marks are approximately12m apart, and the data set covers about 204km of urban streets. The 360 degrees view of each place mark is broken down into four side views and one top view image.

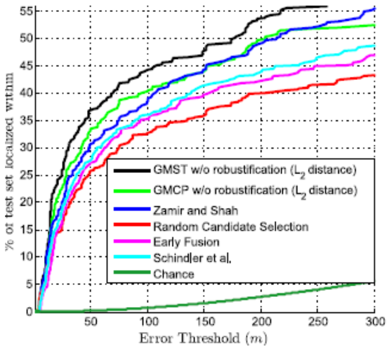

Fig.6.Comparison of the overall geo-localization results using differentglobal features.

9.CONCLUSION

In this paper, a novel framework for geo-localizing images in urban areas was proposed. We developed a multiple-NN feature matching method based on Generalized Minimum Clique Problem. The proposed method is capable of incorporating both global and local features simultaneously. We showed that using a robustified function for finding the distances between the global features is essential when the query image matches multiple reference images with dissimilar global features. Additionally, different types of local features can be used for nominating the NNs. Therefore, our method can be adopted to utilize multiple types of local features inorder to maximize the amount of leveraged information. We evaluated the proposed algorithm on a new reference data set of Google Street View images which will be made available to the public for research purposes.

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