CHARACTERIZING THE TRAFFIC DENSITY AND ITS EVOLUTION THROUGH MOVING OBJECT TRAJECTORIES

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Abstract: Managing and mining data derived from moving objects is becoming an important issue in the last years. In this paper, we are interested in mining trajectories of moving objects such as vehicles in the road network. We propose a method for discovering dense routes by clustering similar road sections according to both traffic and topology in each time period. The traffic estimation is based on the collected object trajectories. We also propose a characterization approach of the temporal evolution of dense routes by a graph connecting dense routes over consecutive time periods. This graph is labeled by the degree of evolution. We have implemented and tested the proposed algorithms, which have shown their effectiveness and efficiency.

1 INTRODUCTION

Managing the location of moving objects is an important issue in several applications mainly in transport. Some applications meant to monitor and forecast the traffic use fleets of vehicles equipped with GPS as probe vehicles, generating Floating Car Data. In this paper, we focus on moving objects (MO) that follows a (road) network - so-called network constraint MO- predominant is real world. An effective and scalable analysis of such large size dataset is a great challenge today. This has motivated research on spatio-temporal data mining aiming at discovering meaningful knowledge from this MO data. Trajectory clustering (Lee et al., 2007) is part of these researches and is one subject of this paper. The other part is the use of the clusters in assessing the traffic density and tracking its evolution over the time. Indeed, with the predictable availability of trajectory databases, we believe this could be a better alternative to the analysis of other traffic sounders (such as under-the-road magnetic field sensors). First, it covers all the roads. Second, it does not require any installation or maintenance on the road network and then has a minimal cost.

Some approaches exist for trajectory data mining (Li et al., 2007). However, most of them do not exploit the topology of the underlying network that has an obvious impact of the density propagation. Moreover, they do not account for the evolution of the density over time. Highlighting this evolution results in a meaningful knowledge – as far as we know- has not been peered through before.

Our approach is based on two assumptions: the first is that knowing the statistics on the traffic density on the network would enable to orient the grouping road sections by density resulting in dense routes, then the second is that the dense routes interact with each other in time, which may fully describe the evolution of the network density.

In (Kharrat et al., 2008), we presented a clustering algorithm applied to road sections in order to discover dense routes, though without considering the time aspect. As an extension of this algorithm, we propose here a method to discover dense routes by clustering nearby sections that show similar traffic density for each time interval. The traffic is assessed thanks to the collected spatiotemporal trajectories. Moreover, we deal with the time evolution of dense routes and characterize it through a labeled graph.

Basically, the main contributions of this paper are those mentioned below:

– We define some new similarity functions

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– We propose a method to cluster the road sections based upon the network density statistics. Unlike some existing work, this clustering takes into account the orientation of the trajectory. Besides, this method utilizes the network topology to create relevant clusters.

– We propose a model to assess the evolution for dense route pairs at two consecutive time intervals.

– We propose a graph conveying the evolution as a mean to describe the information in a synthetic manner and to question the evolution of the density through the whole network.

The rest of the paper is structured as follows. We describe a few preliminary concepts in section 2. In section 3, we present the first step concerning the clustering of road sections. The second step related to the evolution graph construction is presented in section 4. In section 5, we present the result of our experimental study. Finally, section 6 concludes this paper and sketches some future orientations.

2 PRELIMINARIES

The representation of the network is given by the set of road sections. The road section is represented through a graph *NG (N, S)*. *S* is the set of directed segments, where each one represents the smallest unit of road section. *N* is the set of nodes, where each one represents a road junction.

Besides, knowing the set of trajectories, we compute a matrix of transitions for the road network at each time interval. This tells how many times the junction have been taken for each turning movement (i.e. between each pair of adjacent sections), by reporting the number of moving objects going from one section to another at each time interval. This matrix is denoted *M* and *M(i,j)* represents the number of moving objects passing through S_i to section S_j within the interval It_n ($n \in \{1,...,k\}$, k stands for the number of time intervals). We also denote S_{ij} the transition (or turning movement) from S_i to S_j.

We adopt a symbolic representation of the trajectories as in (Du Mouza C. and P. Rigaux, 2004), (Wan T., K. Zeitouni, 2005). In this model, a moving object trajectory *tr* is described by an identifier (*tid*) and a sequence of symbols where each one refers to a road section (S_i), followed by a temporal identifier (t_i) referring the time of entry of the trajectory *tid* to S_i:

$$tr = (tid\ , <(S_{i1}\ t_{j1}), (S_{i2}\ t_{j2}), \ldots, (S_{ik}\ t_{jk})>) \text{ with } S_{in} \in S$$

The order of symbols in the sequence above shows the movement direction.

Concerning the similarity measure adopted in this work, we define the similarity (Trans_sim) at the level of the network for two adjacent transitions S_{ij} and S_{jk} as the difference of their density values:

$$\text{Trans\_sim}\ (S_{ij}, S_{uv}) = |M(i,j) - M(j,k)| \qquad (1)$$

While the similarity between nonadjacent transitions is null:

$$\text{Trans\_sim}\ (S_{ij}, S_{uv}) = 0 \text{ if } i \neq v \text{ and } j \neq u \qquad (2)$$

We define another similarity measure between dense routes (Route_sim). It allows comparing the dense route. Two routes are considered similar (with a similarity equal to 1) if they share at least one road section that corresponds to two successive time intervals. Otherwise, their similarity is null.

3 SECTION CLUSTERING

We call our proposed algorithm NETSCAN. It carries out the clustering of dense sections and incorporates them by forming dense routes. It is inspired from the density based clustering principle introduced with DBSCAN algorithm (Ester et al., 1996), while applying it to road sections. It takes as input the set of sections that constitute the road network, the spatiotemporal transitions matrix associated with each time interval, a density threshold α and a similarity threshold ε between the transition densities. NETSCAN finds firstly the dense transitions, i.e. those having maximum value. Afterwards, for each dense transition, it groups the connected segments and transitions that have similar densities, thus creating dense routes.

The process begins with the transition having the maximal density. Then, it begins searching the connected transitions in both ways in order to find those with a density ε near to the maximal one. To insure the non reuse of transitions that are included in dense routes, they are marked at the first assignment.

The extension of a dense route is done in both ways if the constraints are verified, i.e., the candidate transition is only marked if it respects the α and ε thresholds. The obtained segment clusters correspond to the densest routes in the network. This procedure is performed again for each time interval. The dense routes are represented as a sequence of segments, the same as with the trajectories. Each segment is identified by an associated symbol.

4 DENSE ROUTE EVOLUTION

This section presents our second algorithm called DENSITYLINK corresponding to discovered links between dense routes on successive periods of time. Algorithm DENSITYLINK allows characterizing the evolution of the dense road network. For example, to reveal displacement, extension, reduction, appearance or disappearance of density zones along time. It is based on the dense routes obtained by NETSCAN algorithm, presented in the previous section. The algorithm builds a graph G that binds the dense routes. Two routes are directly linked in this graph if they share the same route in the network at consecutive periods. Thus, it is possible to find the origin of a density zone (in order to avoid it, for example) or to know its effects in order to predict the future density. Formally, we define the evolution graph as a labeled graph G(C,E,W) where C is the set of nodes, each node is a dense route (i.e. a cluster of road sections). E is the set of edges where E = (c, c') means an evolution link from c to c'. W is a set of labels w that represents the evolution weight of edge E.

The algorithm takes as input the set of dense routes distributed on the different time intervals. This part will be used to follow the evolution of these routes during time. It will then seek for each dense route in a time interval it_n those that are similar in the interval it_{n+1}. This similarity is based on the Route_sim definition given in section 2. The final result is a density graph where each node represents a state of a dense route at a given time interval and each transition represents the passage from a time interval towards the following interval. Each transition is labeled by two measurements concerning the evolution. The first represents the decrease percentage of road sections, compared to the previous state and the second is the increase percentage of road sections. These measurements indicate the degree of change of a dense route: extension, reduction, displacement or absence of change.

5 TESTS AND VALIDATION

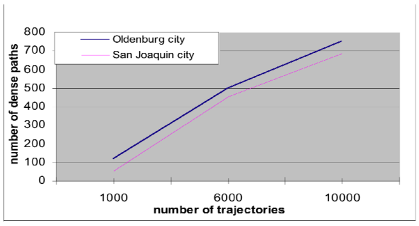
The experimentation uses synthetic trajectory data simulated on real map of a road network, which have thanks to the data generator of Brinkhoff (Brinkhoff, 2002). Based on the road network of San Joaquin (24123 segments of roads and 18496 nodes) and that of Oldenburg (7035 segments of roads and 6105 nodes), we produced various data files of moving objects trajectories to these two roads networks. To show the various densities over time we divided the whole time interval into five partitions. We calculated the density matrices for each data file and each time interval. More precisely, in each matrix, we count the occurrences of the moving objects crossing it to calculate the transition M(i,j). The NETSCAN algorithm was implemented and tested according to various configurations. We varied the number of moving objects between 1000 and 10000 for each city network.

We notice that the number of transitions having a dense traffic (a high value of transitions) is very limited. Figure 1 shows the concentration of the traffic road on the Oldenburg network for the first and the last time intervals. The full number of moving objects in this case is approximately 3500. One can visually notice on the figure that the density decreases while going from the first time interval to the last one.

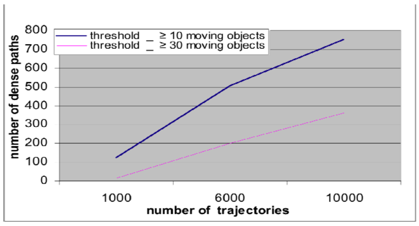
a – Time interval 1 e – Time interval 5

Figure 1: Density evolution on the Oldenburg network.

Generally, the density on the network is sensitive to several criteria. First of all, the number of moving objects on the network, then, the importance and the shape of the network, we had to notice a difference in density by taking the same number of moving objects, but on two different networks. Indeed, figure 2 shows that with 1000 trajectories, the number of dense routes is completely different, in Oldenburg city this number is 119 and in the San Joaquin city this number is rather 55. Lastly, the density also depends on the input parameters chosen by the user, as shown in the figure 2b. The first parameter α specifies the minimum required density in a transition of a route and the second ε specifies the maximum variation of density between connected sections.



a – Impact of the network on the number of dense routes



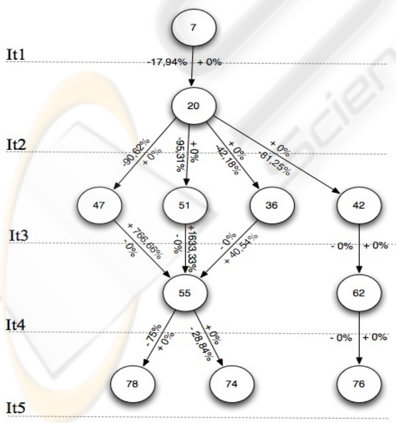
b – Impact of parameter α on the number of dense routes

Figure 2: Sensitivity of the dense routes.

By using the same dataset for the two algorithms, the obtained results in this experimentation -represented in the form of graphs- trace the evolution of a dense route through time. Figure 3 shows the state of a part of the network San Joaquin during the first (a) and the third (b) time interval as well as the corresponding graph (c).

a- Time interval 1

b- Time interval 3



c- Evolution graph

Figure 3: Evolution graph starting from the dense route 7.

6 CONCLUSIONS AND PERSPECTIVES

This paper proposes a new approach for spatiotemporal data mining. More precisely, it adapts the clustering density based technique to network constraint moving objects and organizes the clusters (dense routes) through a graph of temporal evolution. This approach performs in two steps. The first deals with the moving object statistics on the road network and its topology in order to derive the densest routes in predefined time intervals. The second part compares the intersected dense routes in order to organize them as a graph of density evolution. In future, we will explore further analysis of this graph, such as transitive closure to highlight indirect impact of the density and its propagation in the network over the whole day. Another issue is to automatically partition data to relevant time intervals, and to characterize the periodicity of the density and its propagation.

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