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AUTOMATIC DETECTION OF POINTS OF INTEREST USING SPATIO-TERMPORAL DATA MINING

ANAHID BASIRI, STUART MARSH, TERRY MOORE

Nottingham Geospatial Institute, the University of Nottingham, UK
{Anahid.basiri, Staurat.marsh, Terry.Moore}@nottingham.ac.uk

POURIA AMIRIAN

Ordnance Survey, Southampton, UK
pouria.amirian@os.uk

Location Based Services (LBS) are still in their infancy but they are evolving rapidly. It is expected to have more intelligent, adaptive and predictive LBS applications in the future, which can detect users' intentions and understand their needs, demands and responses. To have such intelligent services, LBS applications should be able to understand users' behaviours, preferences and interests automatically and without needing users to be asked to specify them. Then, using users' current situations and previously extracted behaviours, interests and preferences, LBS applications could provide the most appropriate sets of services. This paper shows the application of data mining techniques over anonymous sets of tracking data to recognise mobility behaviours and extract some navigational user preferences such as Point of Interests (PoI) in a format of if-then rules, spatial patterns, models and knowledge. Such knowledge, patterns and models are being used in intelligent navigational services, including navigational decision support applications, smart tourist guides and navigational suggestion making apps.

Key words: Spatio-temporal data mining, Navigation, Trajectory, Knowledge extraction

1 Introduction

Location Based Services (LBS), such as in-vehicle navigation services and Location Based Social Networking (LBSN) applications, have become a part of our daily lives and they are growing rapidly. According to different LBS market reports, surveys and papers, such as the market report produced by The European GNSS Agency (GSA) (The European GNSS Agency (GSA), 2013) and (Chen et al. 2014), Location Based Services will be increasingly intelligent in future. Users look for a service and application that can understand their current situations, predict their needs and demands and provide the most appropriate set of services in the most comfortable way. Users do not want to get distracted by having to specify their current situations and send queries to get relevant responses (Chen et al. 2014). They would like to use an application/service which can detect the current situations (such as current location, travel mode, time of day, interests, mood, etc.), automatically anticipate their needs, preferences and demands (such as nearest gas station or a vacant parking space) using extracted patterns on previous behaviours and also other resources of data, and finally provide relevant information and services (such as navigating them to their preferred destination through streets with less-traffic, finding a vacant parking space near to their workplace or underground station and navigating them to get there).

In order to make current LBS applications and services more intelligent, they need to extract, learn and use patterns and rules (such as rules which associate travel mode with some parameters including speed of movement and trajectory of travel or identifying interests and dislikes of a user based on their history of travels and places visited, etc.). Such rules and patterns help to provide more intelligent sets of services. Data mining techniques are very helpful to identify such patterns, rules, similarities, abnormities and clusters. The results of data mining are more realistic if they are being applied to quite large sets of input data. This paper focuses on extracting patterns, rules, clusters and abnormalities existing in travel and urban mobility. In this regard, the paper applies data mining techniques on anonymised trajectories to identify Points of Interests (PoIs) and use them in a navigational suggestion making service.

In this regard, tracking data, without any reference to a moving user's identity, should be stored. It is possible to use many different anonymisers to make sure that anonymity of data is preserved; in this project K-anonymity (Kalnis, 2007) has been applied. Trajectories can be captured from different resources, such as CCTVs, GNSS embedded in mobile phones or vehicles, accelerometers and so on. Having a huge amount of input data from a variety of resources makes the data management and storage challenging. Due to the volume of the input data, and also the variety of data resources used, the trajectory analysis should be done using big data analytics techniques. Therefore the input data is stored in a Graph database, Neo4j, to have more efficient trajectory data management and analysis trajectory elements (nodes and edges) in comparison with other solutions (Amirian et al. 2015). In order to extract patterns and identify rules, an inference engine is developed to apply big data mining techniques to detect anomalies, identify clusters and classify data (Baiget, 2008), and then extract patterns and rules (Kuntzsch, 2013), (Zhang, 2013). Such information and knowledge can be used in path finding and routing decision making and many other navigational suggestion making applications. For example, if tracking data for a large number of different users can be analysed during a quite long period of time, this may reveal that in a specified time interval, e.g. on 8 a.m. to 10 a.m., many of users' trajectories fit into street networks and, considering their average speed of movement, the first thing to infer would be the travel mode; e.g. driving. This can be considered as rule to be learnt by the system; if the average speed of movement is more than 40 km/h and trajectory matches the street network, then the traveller is not a pedestrian or bicycle, it can be a motor vehicle. If trajectory is matched with bus lines and there are short stops (i.e. speed becomes zero for a short period of time, like 30 seconds) at/close to bus stops then travel mode can be identified as bus. Such rules help in the phase of "recognising a user's current situation".

The inference can be more complicated than a simple if-then rule; it is possible to identify some patterns from input datasets using more complicated data mining techniques. By analysing input trajectories captured from different types of users, it is possible to find out some similarities, abnormalities and more importantly patterns. Patterns are behaviours that repeat; therefore they can be very useful and sometimes essential to anticipate users' demands. For example, after recognising spatial clusters of trajectories with the same travel mode (e.g. car), if analysis shows a sub-cluster of trajectories arrives to a specific area, and then the behaviour of movement changes, e.g. the average speed of movement is reduced dramatically, then it is possible to infer that the specific area is a car park where users have parked their cars and walk to get their next destination. This pattern can be helpful to provide future service, such as making navigational suggestions for parking spaces within the car park. For example, a service could suggest that the user park his/her car in that area an continue the route walking (if it takes less than 10 minutes walking to get the destination) since there is not any other parking space close the destination, or because of congestion on the road network closer to the final destination. One of the most obvious advantages of this is requiring no further knowledge of traffic or urban features; everyone who contributes by providing the trajectory of movement can get such a service in return without needing to have an up-to-date map or urban land-use map of a city.

Take an art gallery as another example. It is possible to track users using indoor positioning technologies, such as wireless networks, RFID network, Bluetooth network or CCTVs, and then analyse their behaviours (Basiri et al. 2014). Having the input data stored over quite long period of time makes it possible to identify points where many users stay immobile for some minutes (possibly to see an artistic object). It would then be possible to suggest to other, new users to visit those points since there might be features there of interest to them, too. The system can alternatively provide navigational instructions or find best paths, which pass such points. The next section discusses the nature of the input data. Then, in section 3, theoretical aspects are explained, including graph databases and spatio-temporal data mining techniques. Finally, section 4 implements the proposed inference system with application to PoI detection.

2 Tracking Data

Having large enough datasets are essential for data mining process. In this regard, input data can include two subsets of data; training data and control data. Training data is used for pattern recognition and rule learning purposes while control data is used to control how learnt rules and recognised pattern can fit into this set of data. Usually at the beginning we have a very large dataset and then it is randomly divided into two sets of training data and control data. After analysing and identifying patterns from training data, inference system employs the extracted patterns on control dataset to evaluate up to what degree the extracted patterns and rules fit into the input control data and how accurate they can model the control data. If the patterns and rules fit very well into the control data, then it is possible to use the pattern for any new dataset. However, in cases of small or incomplete data sets, the selection of the test data may disturb its patterns. Thus, it is better to use only a small amount of data for the purpose of testing.

Larger data sets as input data may lead the inference system to a more realistic results since abnormalities will have less weight in pattern recognition process. There should be a framework in which a large volume anonymous tracking data sets can be stored. Since there is not a universal positioning technique which can get locations of users seamlessly indoors and outdoors with a quite acceptable degree of accuracy, the anonymous tracking data can be collected from different source such as GPS receivers in vehicles, GPS receivers embedded in mobile phones, RFIDs tags and readers, video cameras and CCTVs, Bluetooth networks (Basiri et al., 2014a). Then trajectories are stored in a graph database (Basiri et al., 2015a).

As the name implies graph databases are based on graph theory and employ nodes, properties and edges as their building blocks. The nodes and edges can have properties. In the graph databases various nodes might have different properties. The graph databases are well suited for data, which can be modeled as networks such as road networks, social networks, biological networks and semantic webs. Their main feature is the fact that each node contains a direct pointer to its adjacent node, so no index lookups are necessary for traversing connected data. As a result they can manage huge amount of highly connected data since there is no need for expensive join operations. Some of graph databases support transactions in the way that relational databases support them. In other words the graph database allows the update of a section of the graph in an isolated environment, hiding changes from other processes until the transaction is committed. Trajectory data and in general geospatial data can be modeled as graphs, since graph databases support topology natively, topological relationship (especially connectivity) between geospatial data can be easily managed by this type of NoSQL databases (Amirian et al, 2014). In most GIS workflows, topological relationships play a major role. In addition since each edge in graph database can have different set of properties, they provide flexibility in traversal of network based on various properties. For example it is possible to combine time, distance, number of points of interest and user preferences in finding best path and the mentioned path would be unique for each user. In summary the storage model of graph databases is a graph and there is a need for mapping layer whenever other data structure is needed in application layer.

After storing tracking data, it is very important to make it anonymised using different anonymisers such as K-anonymity (Gruteser, 2003). Most existing anonymisers on tracking data adopt a K-anonymity. In order to do so, the location of the user got by a query and K to the anonymiser, which is a trusted third party (Kalnis , 2007) (Mokbel, 2006) in centralized systems or a peer in decentralized systems (Ghinita, 2007) . The anonymiser removes the ID of the user and cloaks the exact user location. Then anonymiser sends the location and query to the spatial database or location-based services sever.

Now tracking data, i.e. trajectories, are anonymous and stored in the database. It is now possible to use data mining techniques to extract patterns,

3 Pattern Recognition and Knowledge Extraction

In order to find patterns over trajectory data and extract navigational knowledge from it, some of data mining techniques are applied. Data mining is the approaches and methods enabling us to find patterns over available data to extract some knowledge, such as interesting features in a city.

Data mining, as a field at the intersection of computer science and statistics, is a field, which attempts to discover patterns from large data sets. It utilizes methods at the intersection of artificial intelligence, machine learning, statistics, and database systems (Amirian et al. 2014). The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Data mining involves six common classes of tasks:

- Anomaly detection (Outlier/change/deviation detection) – The identification of unusual data records, that might be potential errors or anomalies

- Association rule learning (Dependency modelling) – Searches for relationships between variables. Using association rule learning, one can determine which variable are more related to another. This is sometimes referred to as market basket analysis.

- Clustering – is the task of discovering groups and structures in the data that are in some way or another "similar", without using known structures in the data.

- Classification – is the task of generalizing known structure to apply to new data.

- Regression – Attempts to find a function which models the data with the least error.

- Summarization – providing a more compact representation of the data set, including visualisation and report generation

In this research, firstly, abnormalities and anomalies are detected and stored in a dataset. This dataset includes either trajectories which represent unusual behaviour of users or just errors; therefore they can be simply found using some statistical parameters and also some predefined logical constrains. For examples trajectories or segments of trajectories that represent non-moving users, whose speeds of movements are less than 0.1 m/second for a quite long period of time, e.g. more than 100 minutes, can be stored in the database as unusual behaviour or errors. Such data may generated due to many reasons, such as turning the positioning capability of devices off or not being able to track users due to hardware or infrastructure limitations or even failures. In addition to statistical and logical constrains, there can be some spatial constrains to identify abnormalities and exceptions; for example trajectories with average speed of more than 50 km/h cannot cross buildings and indoors.

After identifying anomalies, exceptions and errors, they are stored in the database, then classification and clustering methods are applied to categorise data into different data sets. According spatial attributes of trajectories, such as location, shape, topological relationship between trajectories and streets networks and also trajectories' bounding rectangles, also according to calculated speed for each segment, and finally according to some temporal characteristics, it is possible to categorise them into different categories. As it is explained in implementation section in more detail, such classes and categories may identify the intention of users. For example, it is possible to deduce from topological relationship between a trajectory and streets network, time of the day and week, and also average speed of movement of user, that user is going to/ getting back from his/her work place or he/she is just visiting the city as a tourist.

Although it is possible to deduce many pieces of useful information from trajectories using above-mentioned methods, there is always a possibility to have miss-matching and inaccuracy. It is possible to categorise a trajectory into a business travel category while it is a touristic sightseeing. On the other hand it is possible not to categorise a trajectory at all since it is not matched with none of above-mentioned rules. In order to have a better understanding of how accurate the recognised patterns and rules are, it is better to have dataset with large number of trajectories. Then divide input data randomly into two sets of training data and control data. After analysing and finding patterns and rules (such as anomaly detection, error detection, clustering and classification, etc.) on the training data, the pattern should be employed on control data to see up to what degree input data and estimated results are similar. Control data is the data set for which the class and category and in general rules and patterns is already available. If very similar it is possible to say we have found the pattern and any new data can be analyse using that pattern. However, in cases of small or incomplete data sets, the selection of the test data may disturb its patterns. Thus, it is better to use only a small amount of data for the purpose of testing. This mode is called leave-one-out method.

The final step of knowledge discovery from data is to verify that the patterns produced by the data mining algorithms occur in the wider data set. Not all patterns found by the data mining algorithms are necessarily valid. It is common for the data mining algorithms to find patterns in the training set which are not present in the general data set. This is called overfitting. To overcome this, the evaluation uses a test set of data on which the data mining algorithm was not trained. The learned patterns are applied to this test set and the resulting output is compared to the desired output. The accuracy of the patterns can then be measured from how many trajectories are correctly classified. A number of statistical methods may be used to evaluate the algorithm, such as ROC curves. If the learned patterns do not meet the desired standards, then it is necessary to re-evaluate and change the pre-processing and data mining steps. If the learned patterns do meet the desired standards, then the final step is to interpret the learned patterns and apply them for new input data or turn them into knowledge.

In order to test and implement above mentioned methods, an ArcGIS add-in has been developed to represent, store, analyse and extract patterns of pedestrians' trajectories based on spatio-temporal data mining methods. Next section shows the implementation of such system.

4 Implementation

One of the widely used applications of ambient services is smart rooms and in general indoor ambient services. In this regard, a conference room has been considered to install cameras. In the room there are five ceiling mounted cameras whose three-dimensional coordinates have been measured accurately. These cameras are allocated in the way that all points and corners of the room are covered. Figure 1 shows one of the cameras' coverage areas.

Fig. 1. One of the mounted cameras' coverage areas

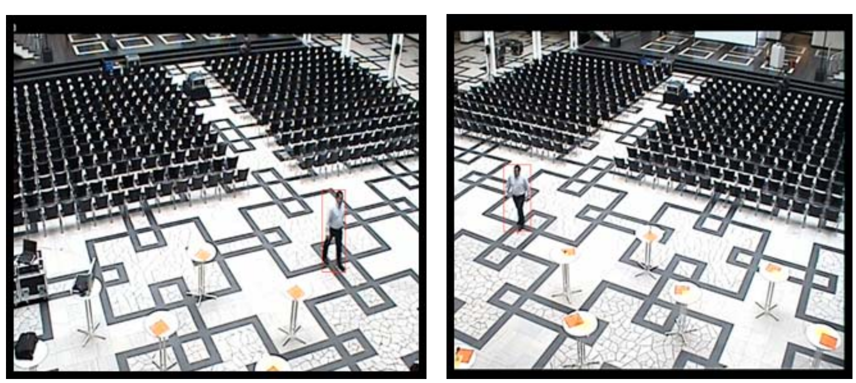

Fig. 2. Minimum bounding rectangle of a user located in the overlapping area of two cameras

In camera installation phase, the final goal was maximizing the room coverage and also having more overlapping area, which is covered by more than one camera. Having overlapping areas is very important since all analysis is doing over anonymous data and users are identified using a random number (Object ID) assigned. So in order to follow the user roaming from one camera's coverage area to another's, it is very important to have an area, which is covered by two cameras to find the corresponding absolute position of a user in overlapping area, as it shown in figure 2.

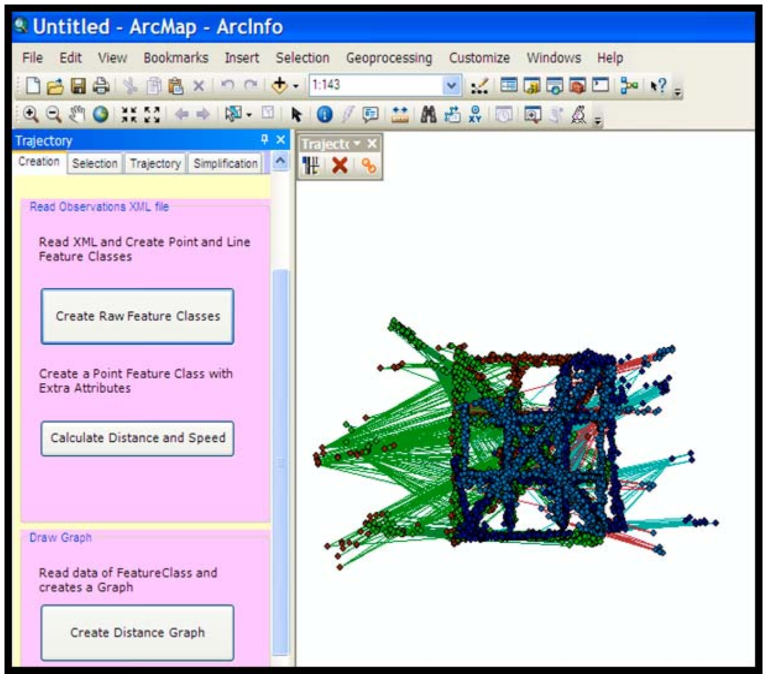

Fig. 3. Trajectory analyser duckable window (developed ArcGIS add-in)

After installation phase, we need to store location and time for every person detected by image processing module. Then detected user's location and corresponding time are stored in a document. Based on such document it is possible to visualise trajectories. In order to do so, an ArcGIS add-in was developed to visualise, analyse and mine the data. As it is illustrated in figure 3, a trajectory analyser douckable window is added to ArcMap. Its first tab Creates a feature class by reading the input XML file. It also can add two columns to the created feature class which calculate distance between every point and the point next to it (length of each segment) and speed of movement of user passing that segment.

The very last button (Create Distance Graph) in Creation tab generates graphs and diagram to visualise some statistical information, such as average speed of movement. Figure 4 shows a graph for speed of movement. As it can be seen in figure 4, minimum, maximum, average and standard deviation are calculated and shown. This graph may help to rule out some of errors and also exclude redundant data. For example if the speed of movement of the user between two points is much more than normal speed of a pedestrian (1.5 m/s), then it is possible to take that segment as error and store it in another dataset since a pedestrian cannot move with such high speed (e.g. 20 m/s). Also it is possible to find points where user has had no movement (speed is near zero) and replace them with one single point with a description of time interval during which user's speed is zero.

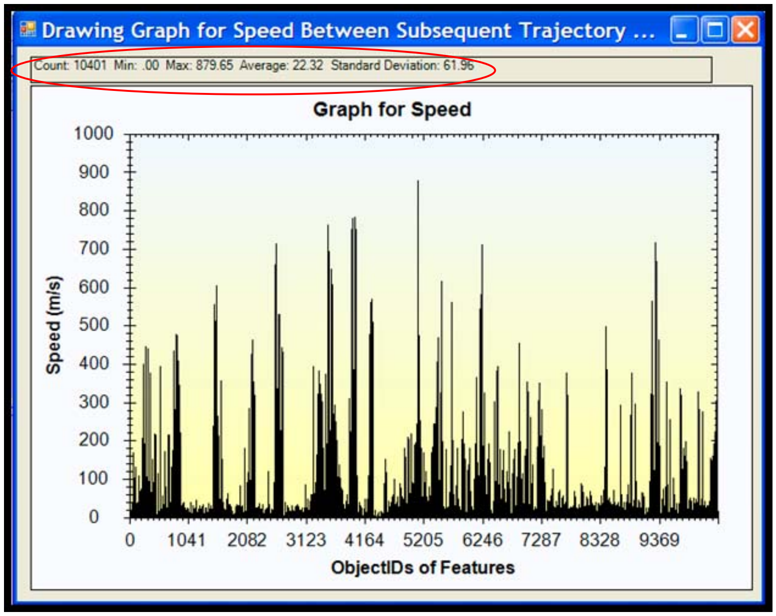

Fig. 4. Graph for speed of movement between every two sequential points

Using such statistical analysis, it is possible to exclude some of errors, which may occur because of image processing and feature matching challenges (such as detecting user's reflection instead of user, etc.), and also manage the data in a better way.

Another challenge in this project is redundant data. It is possible to have more than one trajectory for each user at the same time interval, with different shapes and sizes, since users can be viewed by different cameras synchronously. If two or more cameras detect a person at the same time in their overlapping area, then we will have two or more trajectories stored for that person, as it is shown in figure 5. The simplest policy is to consider all trajectories ignoring this fact that some of them may not show different users' movements since they are redundant data for the same user moving in a same period of time. This policy may lead in having higher weight for trajectories located in overlapping areas. In order to handle this, we need to find only one trajectory, which shows the user's movement as detail as possible. This becomes more complex where there is no link between user and trajectory. Because of privacy issues, there is no link between users and their trajectory. That means, it is not single user ID assigned to user and based on which the corresponding trajectories (got from different cameras) can be identified. In this regard trajectories belong to a single movement made by single user should be identified, and then they should be transformed into one polyline to show user's movement over a period of time.

In order to find the trajectories to be matched and aggregated into one trajectory, we need to find correlated vertices, which represent one object captured by different cameras, and replace them with one vertex. In order to do this, the simplest policy can be finding vertices, which are spatially and temporally near to each other. Because the vertices, which are recorder spatially and temporally near to each other, are more likely to represent one user and the small differences between them can be because of camera synchronisation drift, calibration and instrumental errors. However this approach may be the simplest approach to find trajectories representing a single user's movement, it has got some issues. First of all, and the most important one, is mismatching issue. It is possible to find many trajectories that satisfy the conditions, i.e. captured within quite the same temporal interval and also spatially near, while some of these trajectories belong to another user and they represent another user's movements. In addition, finding the best time interval and also spatial buffering radios for matching process in which trajectories are analysed is quite tricky. Figure 5 shows selection tab in the developed ArcGIS-Add in which allows selecting vertices captured spatially and temporally close to each other. Then a column will be added to the attribute table to show which segments should be matched. As it is shown in figure 5, spatial and temporal thresholds should be given or previously set, for example in figure 5 vertices whose distance from surrounding vertices were less than 2 centimetres and also have been captured in a 100 milliseconds time interval are selected. Finding the best temporal and spatial threshold depends on the applications, movements' characteristics, experts' comments, equipments' configurations and settings, etc.

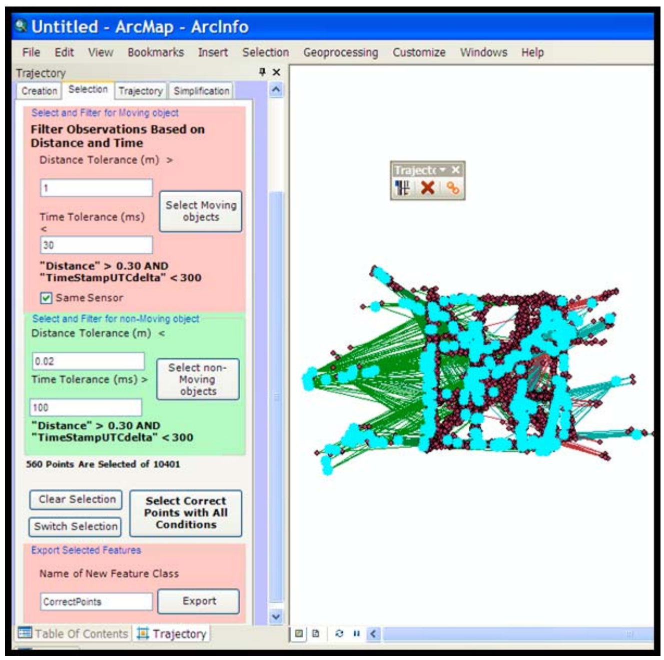

Fig. 5. Finding matched trajectories based on temporal and spatial thresholds

This might be the simplest approach, however because of mismatching and also being so experience and application dependant, makes it unreliable. In this regard, this paper proposes using data mining techniques to find matching segment. This means, introducing fixed grid windows in which segments whose patterns are quite same considered to be matched. In contrast with previous approach which only considers spatial and temporal proximity to find matching segments, this approach considers pattern of movements. Figure 6 shows how two trajectories are found as matching trajectories using this approach. The green trajectory is captured by camera1 and the red trajectory is captured by camera2. As cameras locations, confutations and settings are different they may capture different trajectories with different numbers of vertices, as it shown in figure 6. However the proposed approach considers pattern of movement within a temporal and spatial window. For example the green and the red trajectories in figure 6 can be found as matching trajectories since the general trends and pattern of movement in the predefined window, including four time intervals and a spatial bounding box, is quite same. Those very small noises (which are differences of the trajectories from the general trend) are ignorable according to the predefined settings.

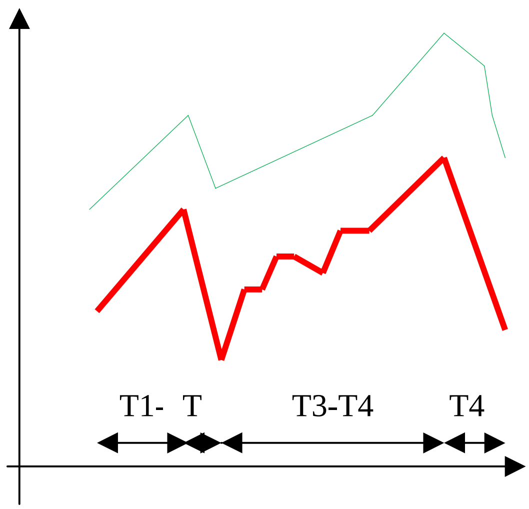

Fig. 6. Two trajectories generated by two cameras for a single user located in the overlapping area of the cameras' coverage

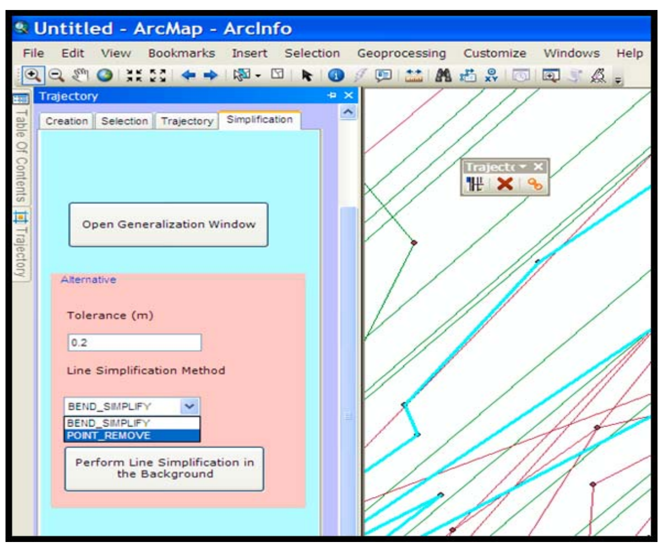

Fig. 7. Finding matched trajectories tab, simplification tab

Both approaches, finding near vertices based on a spatial and temporal threshold and also the pattern-based approach, have been implemented in the developed ArcGIS add in to make choices and also make easier to understand what would be results of both approaches on the same dataset. Figure 7 shows the matching tab, called simplification since it matches segments to reduce redundant data.

Now the data has been pre-analysed and it is possible to define some rules based on which Points of Interests (PoIs) can be extracted. This may be very helpful in tourist guidance or any indoor navigation services. Since cameras (CCTVs) are usually available indoors, especially in galleries and museums. In order to find PoIs, it is possible to select vertices where many users stay for a period of time (probably to see an interesting feature, such as sculpture, painting, etc.). In order to find such points, easily one can use selection tab and select non-moving users. If the number of users who stays in this point (or very close to this point) was more than a threshold, then we can export that point (or area) as a new feature class, called Point of Interests. Again spatial and temporal threshold and also number of users are selected based on the application and experts comments. These PoIs can be used to make navigational suggestions for new comers.

5 Conclusion

Future LBS services will be more anticipatory of users' needs. Users look for a mobile service/application which can monitor or understand their current situations, predict their needs and demands, and then provide the most appropriate set of services in the most comfortable way. This paper describes a method based on data-mining to detect and extract existing patterns over pedestrian trajectories. The trajectories of anonymised users tracked in surveillance cameras are considered as sequences of time-discrete observations of those users' positions. These trajectories are processed to find patterns within pedestrians' movements. For example, it is possible to find attractive/important points or features in a gallery, based on the most common users' trajectories; i.e. where there is no movement over a period of time for many tourists. These points can be considered as point of interests to be applied in giving navigational instructions or suggestions to other users; i.e. it is possible to recommend a new user to go to that point, since many people have visited that location. In order to extract such patterns efficiently from spatio-temporal data of pedestrians, including time and position of users, an ArcGIS add-in has been developed to implement the method. This represents, stores, analyses and extracts patterns of pedestrians' trajectories based on the spatio-temporal data mining methods described in the paper.

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