Similarity in (Spatial, Temporal and) Spatio-Temporal Datasets

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ABSTRACT

Similarity among mobile entities is an important type of query for many application domains. This tutorial provides a comprehensive overview of the different challenges related to assessing the similarity of spatio-temporal objects, along with the corresponding results/techniques.

Categories and Subject Descriptors

I.m [**Computing Methodologies**]: Miscellaneous

General Terms

Algorithms

1. INTRODUCTION

Efficient and effective methods for detecting *similarity* among entities whose spatial attributes change over time are important for a broad range of application domains. But few examples include: – Evolution of geographic and seismic processes and events [58, 59]; Categorization of the movement features of objects from everyday-life (e.g., pedestrians vs. cars) [22]; Particle motions at (sub) molecular level [46, 62, 67]; Time-series describing trends of changes of a particular phenomenon (e.g., financial data) [69].

Technological advances in satellite imaging [76] and Global Positioning Systems (GPS) technologies [12, 54, 57], along with the miniaturization of sensing devices self-organizing in networks [39, 41, 79, 88], enabled generating large volumes of *(location,time)* information pertaining to mobile entities. Different application domains may have different means of storing the spatio-temporal data which, in turn, affects the properties of the algorithms for processing the queries of interest. As an example, Figure 1 presents three scenarios from different domains: a motion of a human playing golf, where the trajectories were captured by two different cameras [70,87]; trajectories obtained by sampling the dynamics of molecular structures [35]; grouping of trajectories from a given Moving Objects Database (MOD) [34] that constitute a *flock* [33]. Despite their heterogeneity, all three examples have some common threads: (1) how to asses the degree of similarity of two trajectories, and (2) how to identify which (groups of) trajectories are more similar among themselves than the rest of the (groups of) trajectories in the dataset. One of the crucial aspects, reflecting the semantics of the problem-domain and affecting both the efficiency and effectiveness of the corresponding algorithms [21] is the selection of the *distance function*. The properties of the distance function have a strong impact on the indexing methodologies and the respective algorithms used for classification, clustering and approximation [27, 36, 42, 45, 84]. The main objectives of this tutorial are:

1. Provide a comprehensive overview of different research issues and solutions addressing various aspects of the problem of assessing the similarity of spatio-temporal data. Address in detail the impact of application contexts on the distance functions and techniques used for similarity detection.
2. Overview the techniques for similarity detection in spatial and temporal datasets – before focusing on spatio-temporal data – thereby providing a "historic" context and balancing the *breadth* and the *depth* of the presentation, thereby catering to a broader-interests audience.

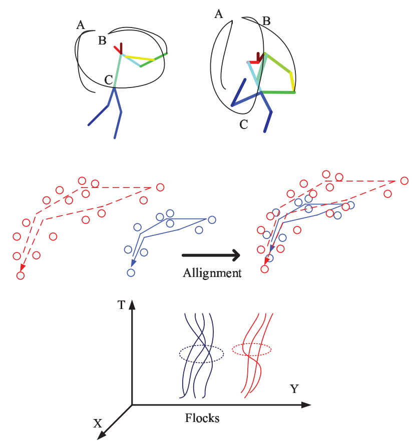

Figure 1: Similarity of Motions in Different Application Domains

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3. Present several open challenges related to spatio-temporal similarity in different application domains and with the different (heterogeneous) data features and semantics.

2. TUTORIAL OUTLINE

We now outline the main themes addressed in the tutorial:

• **Motivation – Applications Settings**: We motivate the importance of the problem of efficiently detecting the similarity of mobile entities by presenting its relevance in several application domains [22, 39, 46, 58, 59, 62, 67, 70, 79, 87, 88].

• **Similarity of Spatial/Geometric Entities**: We review some results from the Computational Geometry community related to detecting the similarity of 2D (and higher-dimensional) shapes [2, 3, 5]along with evaluation modulo certain *transformations* – i.e., rotation, translation or scaling [18, 85]along with sub-optimal matching – with algorithms executing much faster than the optimal matching [32, 37].

• **Similarity and Distance Functions**: Apparently, the traditional Hausdorff distance [3] is too "static" for a wide range of applications, and we review the problem of efficiently evaluating the Fréchet distance [1, 4, 7, 24, 61], along with the issues of uncertainty of spatio-temporal data [75], and the earth-movers distance [68, 71].

• **Time-Series Data**: The problem of efficient evaluation of similarity is central to the management of time series data, and the two important aspects are the *representation methods*, and the *similarity measures* [21]. Representation methods aim at reducing the dimensionality, without significantly distorting the dat characteristics [27, 43, 52], whereas the similarity measures balance the efficiency and the accuracy of classification [9, 16, 28, 44, 60].

• **Similarity of Moving Objects Trajectories**: Unlike the time-series data, the motion of the objects in many application domains occurs in two (and higher) dimensions, and a large body of works from MOD and GIS communities [6, 26, 73, 78, 80, 82, 83]. have have focused on similarity in such settings. We first formalize the problem of similarity among trajectories [26, 28, 78] based on their representation [25], including segmenting them for applying different distance-based techniques [6]. We also address the specifics of detecting the similarity among objects whose motion is spatially constrained to an existing road-network [13, 72], along with the robustness issues [81, 82]. Lastly, we present techniques for assessing similarity of trajectories under certain transformations (rotations and translations) [80, 83] and sub-optimal solutions [38, 73].

• **Trajectories' Data Mining**: We overview some research results related to clustering and classification of trajectories [23, 50, 51, 56, 64] and different spatio-temporal distance operators for mining purposes [66]. We also address issues arising with sub-trajectories [11, 49], along with outliers/anomalies detection [29, 90], as well as bundling flocks and convoys of trajectories [33, 40]. The last portion of this part of the tutorial addresses issues related to warehousing of spatio-temporal data [10, 55, 77].

• **Domain Constraints**: This part of the tutorial focuses on specific constraints arising in particular application domains, and their impact on calculating the similarity of the motions: Wireless Sensor Networks (WSN) where tracking is done by trilateration and the important aspect of the problem is balancing the efficiency of transmission with (im)precision and freshness of the data in the sink [31, 48, 65, 74, 86, 89, 91], along with clustering and warehousing [15, 63].

• **Challenges**: The tutorial concludes with an overview of some open problems and application domains: deformable shapes [17], the OLAP-related role of similarity [8], the incorporation of a map-data [14], traffic management [20, 30, 47, 53] and cloud-settings [19].

We re-iterate that the goal of this 180 minutes tutorial is to present a framework in which the rich history of the problem of similarity of motion can be cast, discuss its role in various applications, and outline example solutions to certain specific problems – thereby balancing its breadth vs. depth trade-off(s). A related three-hours tutorial ("On the Similarity of Motions") by the same authors was presented at the MDM 2010 conference. The current tutorial has three main differences:

1. We have updated that version to include more recent results.
2. We have added two sections – in addition to updating the sections from the prior version.
3. We have addressed a larger group of application domains.

3. PRESENTERS BIOS

Dimitrios Gunopulos received his PhD from Princeton University in 1995 and has held positions at the Max-Planck-Institut for Informatics, the IBM Almaden Research Center, and at the Department of Computer Science and Engineering in the University of California Riverside. His main research interests are in the areas of Data Mining, Knowledge Discovery in Databases, Databases, Sensor Networks, Peer-to- Peer systems, and Algorithms, and he has co-authored a book and over 160 publications in refereed conferences and journals. He has served as a General co-Chair in the IEEE ICDM 2010 conference, as a PC co-Chair in the ECML/PKDD 2011, IEEE ICDM 2008, ACM SIGKDD 2006, SSDBM 2003, and DMKD 2000 conferences, and as an associate Editor at the IEEE TKDE, IEEE TPDS, and ACM TKDD journals.

Goce Trajcevski received his PhD from the University of Illinois at Chicago in 2002 and has participated in both NSF and industry-funded research projects (with BEA Corp. and Northrop Grumman Corp.). His main research interests are in the areas of Mobile Data Management, Uncertainty Management and Sensor Networks and, in addition to book-chapters, he has co-authored over 60 publications in refereed conferences and journals and has received two best paper awards (CoopIS 2000 and MDM 2010). He was part of the organizing committees of ACM SIGMOD 2006, IEEE MDM2011, IEEE MDM 2012 and ACM GIS 2011 and has served in the program committees in numerous conferences and workshops.

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