

Vision Trajectories: Scene, Method and Dataset

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ABSTRACT

Nowadays, the widely existence of vision trajectories like handwriting [8], sports player running [9] and pedestrian moving [2] requires efficient trajectory database management. And in this paper, we will first introduce the application scenes of vision trajectory. Then we'll discuss the difficulty in the process of vision trajectory similarity searching, like trajectory normalization and dynamic time warping (DTW) computation complexity. After that, a brief description of available datasets would be given.

CCS CONCEPTS

• Information systems → Database design and models.

KEYWORDS

database management, handwriting trajectories

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1 INTRODUCTION

Handwritten trajectories can also be applied to computer-human interactions [8]. The paper proposes a novel way to control computers by moving fingers in the air. They demonstrate this human input approach through an example application of handwriting recognition. A 3D finger moving trajectory is captured by the sensor and then search for the most similar trajectory in the standard character trackings database. Because while capturing, there is no explicit gesture that indicates when a character starts or stops, so that each subtrajectory should be compared with all the standard trackings. While the dynamic time warping (DTW) based similarity search algorithm is so time-consuming that searching in a 160-trajectories dataset may take about 10 seconds. So a more efficient way to manage these trajectory data is in need, especially when we are dealing with database that contains several millions of handwritten trackings.

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Table 1: Statistics of CASIA Database

dataset	writers	character samples		
		total	symbol	Chinese/class
OLHWDB1.0	420	1,694,741	71,806	1,622,935/3,866
OLHWDB1.1	300	1,174,364	51,232	1,123,132/3,755
OLHWDB1.2	300	1,042,912	51,181	991,731/3,319
total	1,020	3,912,017	174,219	3,737,798/7,185

2 NORMALIZATION

3 DYNAMIC TIME WARPING

In measuring trajectory similarity, Dynamic Time Warping (DTW) is a well accepted method. Different from Euclidean Distance, DTW consider matching points within a certain time window, that's also how the name "warping" comes. But the expense of computation is very large, and several optimizations are proposed in [1, 7], including lower bound pruning, early abandoning Z-Normalization, reordering early abandoning, reversing the Query/Document role in LB_{keogh} and cascading lower bounds. Even though, the approximate computing complexity of DTW is still $O(mn)$, where m and n represent the length of query and candidate sequences separately.

4 DATASETS

There are datasets of vision trajectories of considerable size. For example, the CASIA database of Chinese character handwriting trajectories [5] consists of over 160 million trajectories of more than 3000 classes. And trajectory databases of other languages are also available, like English [6], Japanese [4], Vietnamese [3], etc. In Table 1, we show the statistics of CASIA database.

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