# Vision Trajectories

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## ABSTRACT

Nowadays, trajectories extracted from vision objects including image and videos like handwriting trajectory [6, 9], sports player running trajectory [11], vehicle driving trajectory [5] and pedestrain moving track [2] require an efficient trajectory management database. While the current trajectory search engine like [10] can not be transfered to this new task simply, because of some properties shared amongst vision trajectories. For example, the dense distribution within a relatively small area compared with traffic trajectories. 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 intereactions [9]. 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 similairty, 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, 8], including lower bound pruning, early abandoning Z-Normalization, reordering early abandoning, reversing the Query/Document role in $LB_{keogh}$ and casacading 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 aequences separately.

## 4 DATASETS

There are datasets of vision trajectories of considerable size. For example, the CASIA database of Chinese character handwriting trajectories [6] consists of over 160 million trajectories of more than 3000 classes. And trajectory databases of other languages are also available, like English [7], Japanese [4], Vietnamese [3], etc. In **Table 1**, we show the statistics of CASIA database.

## REFERENCES

[1] Ada Wai-Chee Fu, Eamonn J. Keogh, Leo Yung Hang Lau, Chotirat (Ann) Ratanamahatana, and Raymond Chi-Wing Wong. 2008. Scaling and time warping in time series querying. *VLDB J.* 17, 4 (2008), 899–921.

[2] Agrim Gupta, Justin Johnson, Li Fei-Fei, Silvio Savarese, and Alexandre Alahi. 2018. Social GAN: Socially Acceptable Trajectories With Generative Adversarial Networks. In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018.* 2255–2264.

[3] Nguyen Tuan Hung. 2016. TUAT Nakagawa Lab. HANDS - Vietnamese Online Handwriting Database (HANDS-VNOnDB). Retrieved August 26, 2019 from http://tc11.cvc.uab.es/datasets/HANDS-VNOnDB_1

[4] Stefan Jäger and Masaki Nakagawa. 2001. Two On-Line Japanese Character Databases in Unipen Format. In *6th International Conference on Document Analysis and Recognition (ICDAR 2001), 10-13 September 2001, Seattle, WA, USA.* 566–571.

[5] Robert Krajewski, Julian Bock, Laurent Kloeker, and Lutz Eckstein. 2018. The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems. In *2018 IEEE 21st International Conference on Intelligent Transportation Systems (ITSC).*

[6] Cheng-Lin Liu, Fei Yin, Da-Han Wang, and Qiu-Feng Wang. 2011. CASIA Online and Offline Chinese Handwriting Databases. In *2011 International Conference on Document Analysis and Recognition, ICDAR 2011, Beijing, China, September 18-21, 2011*. 37–41.

[7] David Llorens, Federico Prat, Andrés Marzal, Juan Miguel Vilar, María José Castro, Juan-Carlos Amengual, Sergio Barrachina, Antonio Castellanos, Salvador España Boquera, J. A. Gómez, Jorge Gorbe-Moya, Albert Gordo, Vicente Palazón, Guillermo Peris, Rafael Ramos-Garijo, and Francisco Zamora-Martínez. 2008. The UJIpenchars Database: a Pen-Based Database of Isolated Handwritten Characters. In *Proceedings of the International Conference on Language Resources and Evaluation, LREC 2008, 26 May - 1 June 2008, Marrakech, Morocco.*

[8] Thanawin Rakthanmanon, Bilson J. L. Campana, Abdullah Mueen, Gustavo E. A. P. A. Batista, M. Brandon Westover, Qiang Zhu, Jesin Zakaria, and Eamonn J. Keogh. 2012. Searching and mining trillions of time series subsequences under dynamic time warping. In *The 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '12, Beijing, China, August 12-16, 2012*. 262–270.

[9] Sharad Vikram, Lei Li, and Stuart J. Russell. 2013. Writing and sketching in the air, recognizing and controlling on the fly. In *2013 ACM SIGCHI Conference on Human Factors in Computing Systems, CHI '13, Paris, France, April 27 - May 2, 2013, Extended Abstracts*. 1179–1184.

[10] Sheng Wang, Zhifeng Bao, J. Shane Culpepper, Zizhe Xie, Qizhi Liu, and Xiaolin Qin. 2018. Torch: A Search Engine for Trajectory Data. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR 2018, Ann Arbor, MI, USA, July 08-12, 2018*. 535–544.

[11] Zheng Wang, Cheng Long, Gao Cong, and Ce Ju. 2019. Effective and Efficient Sports Play Retrieval with Deep Representation Learning. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2019, Anchorage, AK, USA, August 4-8, 2019*. 499–509.