Online Writing Recognition – Review: Trajectory-Based Modeling and Recognition of Characters and Words

Deval Verma[1], Ajay Kumar[2]
[1]Lincoln University College,47301, Petaling Jaya, Selangor Darun Ehsan, Malaysia
[2] IILM University, Greater Noida, India
[1]Email ID: pdf.deval@lincoln.edu.my ; [2] Email ID: ajay.phdcse@gmail.com

Abstract: Neurons in the brain's nerve system regulate handwriting, which reflects a person's psychology and personality. User authentication, the evaluation of neurodegenerative conditions, and the categorization of handedness, gender, and age groups are only a few of the uses for this special quality. Conventional authentication methods are susceptible to security breaches because they involve fingerprints, memorization, and information leaking. Online handwriting is a contemporary human-computer interaction technique that allows users to write on the surface in an unconstrained, natural way. Due to its unique characteristics, pen-based online handwriting is far more challenging than typical 2D handwriting systems that rely on ink and paper.

Keywords: 2D handwriting; neurodegenerative; Online handwriting; Pen-based online handwriting

Introduction

In last few months, Online handwriting-based system as a first handpicked device seemed in the market has drawn a lot of interest from people in various fields of communication [1]. Although consumers find pen interfaces to be highly real, handwriting identification remains a challenging process, because of the COVID-19 pandemic, many companies and educational institutions worldwide have switched to internet platforms. For people accustomed to working in an office or learning in a classroom, the transition is difficult and confusing. Using the appropriate digital tools may greatly increase the accessibility and productivity of online work. However, academics find handwriting identification to be difficult undertaking. As a result, researchers are under pressure to develop more effective identification methods. Online handwriting, often referred to as handwriting in three dimensions, is handwriting done with a pen on a computer [2,3]. This leads to the recognition of handwritten characters obtained from sensitive surface in the form of trajectories. 3D motion trajectory recognition is one of the elementary concepts due to its substantial applications, together with human computer interaction [4,5,6].

Related work

An online recognition method based on pen up and down motions is called 3D motion trajectory classification. Essentially, human input has a definite start and finish. Nonetheless, researchers employ a variety of strategies for practical recognition. There is much more thorough study in [8]. A hierarchical architecture for fitting a Bezier curve for 3D data analysis and recognition has been developed by the authors in [9]. This Bezier curve is fitted for viewing using translation and rotation.

Many researchers employ UNIPEN data and are limited to a single character input [1]. description of frequently used characteristics such as velocity, bitmaps, moments, orientation maps, normalized coordinates, cross-ing of stroke points, and bitmaps [2,3,4,5,6,7,8,9,10,11,16].

Table 1. Compares this work with the related work or previous research by other researchers

Reference	**Representation / Feature Type**	**Methodology**	**Dataset**	**Target Application**	**Key Observations/ Results**
2004, [9]	Geometric invariance (rotation, scale, translation)	Bézier curve–based curve fitting	3D hand gesture dataset	Visualization and navigation	Achieved a recognition accuracy of 97.9%
2008, [11]	Motion primitives with temporal variability	Factorial Hidden Markov Model (HMM)	300 handwritten ‘p’ samples	Robotic motion control	Enables precise modeling of temporal dynamics
2009, [12]	Elliptical motion class representation	Expectation–Maximization (EM) combined with Iterative Pairwise Replacement Algorithm (IPRA) using GMM	UCI Auslan sign trajectory dataset	Signature modeling and robot learning	Motion classes effectively represented as sequences of ellipses
2010, [13]	Invariant motion descriptors	Discrete matching techniques	UCI Auslan sign trajectory dataset	Robotics applications	Demonstrates improved recognition performance
2012, [14]	Salient motion feature extraction	Continuous Dynamic Time Warping (CDTW)	Large UCI sign trajectory dataset	Human motion and gesture analysis	Reported class recognition ratio of 2.63%
2015, [15]	Distance and area integral invariants	Distance-based similarity function	HDM05 and MHAD datasets	Human and robot motion tracking	Produces robust and reliable results
2016, [17]	Shapelet-based time-series representation	Nearest-neighbor distance classifier	45 UCR time-series datasets	Gesture recognition; medical and health informatics	Achieves superior recognition accuracy

2017, [18], Shen et al.	Spatio-temporal neural encoding	Recurrent Spiking Neural Network (RSNN)	CHAR3D dataset (2,858 characters)	Character recognition	Yields higher average recognition accuracy
2017, [19], Yu et al.	Dynamic features	(CTLSTM) model	CHAR3D dataset human action dataset	Recognition of human action	Better recognition accuracy
2017, [20] Guo et al.	(DKSM) and histogram of gradients (HOG) descriptor	Support vector machine (svm)	CHAR3D and IP3D datasets	Motion analysis of robots and moving objects	98.21% at CHAR3D, 84.18% at IP3D
2019, [21]	Curvature and torsion of thetrajectory	Drichlet mixture model	Three MoCap datasets	To recognize human motions	Area under curve are 76.5%, 91.92%, 98.44%, 98.9%.

The brief literature review based on the applications of 2D/3D characters and 3D word recognition is given in Table 1. The proposed system effectively employs normal distribution of data to identify the most effective statistical collection of features. Moreover, geometric properties and direction of writing pen are also used for trajectory classification.

Key Contribution

The following research gaps have been identified from the literature survey based on the research contribution of various authors in the field of 2D/3D character and 3D word recognition.

Researchers frequently employ characteristics like writing direction, curvature, and 3D points in 3D word recognition. Nevertheless, the use of other characteristics hasn't been proven in literature yet. Additionally, there hasn't been much attention to the best feature selection. Since it is challenging to identify the start and finish of segments, unsupervised learning and data-driven methods are usually employed. Hidden Markov Models or a combination of HMMs and neural networks are used in statistical approaches to character recognition.

Results and Discussions

Other relevant research demonstrates the need for a pen-up/pen-down gesture to identify the start and finish of significant input. Pen up/pen down gestures are used by many current online handwriting recognition methods to window the input data. In essence, human input has a defined beginning and finish. This is not an assumption made in this work. Segmenting the data points is one method employed in the procedure.

This survey work concludes by introducing a sophisticated user identification system that evaluates real-time numerical data gathered by a pen-tablet sensor and handwriting time series. The system's successful user identification is demonstrated by encouraging outcomes. The use of geometric features for 3D character identification has been highlighted in earlier research. But there hasn't been much talk about geometry, structural and angular characteristics, together with their combinations for identification.

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