International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 1 Issue 4 ǁ August. 2013 ǁ PP.48-52

On-Line Handwriting Recognition: Current Developments and Future Prospects

Jagin M. Patel[1] and Bharat C. Patel[2]
[1]M. K. Institute of Computer studies, Bharuch, Gujarat, India.
[2]Smt. Tanuben & Dr Manubhai Trivedi College of Information Science, Surat, Gujarat, India.
E-mail: [1]jagin_2k@yahoo.com , [2]patelbharat99@yahoo.co.in

Abstract: *On-line handwriting recognition has been a subject of research, aiming to enable machines to interpret and understand human handwriting in real-time. This paper provides an overview of the advancements and challenges in on-line handwriting recognition. We present a comprehensive review of the methodologies, and systems developed, highlighting the key approaches and applications. Furthermore, we discuss the major challenges faced by researchers and the directions for future research in on-line handwriting recognition.*
Keywords: *On-Line Handwriting Recognition, Challenges, future of On-Line Handwriting Recognition*

I. INTRODUCTION

On-line handwriting recognition refers to the process of automatically interpreting and understanding human handwriting as it is written in real-time, while Offline handwriting recognition is carried out after the writing is finished. Unlike off-line handwriting recognition, which analyzes scanned images of handwritten text, on-line handwriting recognition involves capturing dynamic information such as pen strokes, timing, and pressure during the writing process.

Handwritten recognition has become increasingly popular due to the development of devices such as Smartphones, tablets etc., that can digitize data entered. The recognition of on-line handwriting has gained significant attention in research and development due to its potential applications in various domains. On-line handwriting recognition systems aim to convert handwritten strokes into digital text or symbolic representations. By enabling machines to understand and interpret human handwriting, on-line handwriting recognition facilitates seamless interaction with digital devices, enhances productivity, and expands the possibilities of human-computer interaction.

This is the introductory section. Section 2 gives literature on on-line handwritten recognition, section 3 discuss On-line handwriting recognition systems, section 4 discuss challenges and the last section gives an overview of Applications and Future directions in On-line Handwriting Recognition

II. LITERATURE ON ON-LINE HANDWRITTEN RECOGNITION

A. Overview

In the year 2004, Sivaramakrishnan and Bhattacharyya [1], developed system for online Tamil handwritten character recognition which used kernel based approach and employed two-step system for interpolation and resampling with SVM classification. Fathallah and Plamondon [2] perform various tests on the PENPAD 310 system.

Graves et. al. [3] uses HMMs for online handwriting recognition with varying degrees of success. Support Vector Machines (SVMs) [4] have recently become an effective method for categorising fixed-length vectors.

Bothe et. al. [5] has performed on-line handwriting recognition in which handwriting is characterised as a time sequence of vectors. Every sample point in time is represented by a feature vector that stores the pen tip's horizontal and vertical coordinates in relation to the writing surface. They used SVM and kNN for classification. They also explore how parallelization can enhance their performance and how these enhancements might be applied to a mobile device.

Pavlidis et. al. [6] used physics-based shape metamorphosis for on-line handwriting recognition. Mondal et. al. [7] proposed methods to recognise four Indian scripts Tamil, Bangla, Devanagari, and Telugu. This method uses point-float and direction code histogram features. Classification is done using Nearest Neighbour, Multilayer Perceptron and Hidden Markov Model.

Toselli et. al. [8] proposed a system for On-Line Tamil Handwriting Recognition which is based on continuous density HMM. Many very good summary for on-line handwritten recognition is found in survey papers [2,9,10,11].

The main issue with character segmentation is how difficult it is to pinpoint each character's beginning and ending. To deal with this, a few authors suggested Unsupervised learning [12, 13], data-driven knowledge-based algorithms [14, 15] etc., methodologies. However, they are still unsatisfactory for the majority of applications.

Anquetil and Bouchereau [16] proposed "ResifCar" which is an integration of an On-line Handwriting Recognition with a goal to implement an accurate handwriting recognizer into mobile devices. Hierarchical fuzzy modelling is used to create a compact and robust knowledge representation. The decision process is based on a fuzzy inference system which reduces calculating.

Jianying et. al. [17] proposed a system for on-line handwriting recognition which uses long-range features and local features. These two features are combined and used in integrating the segmentation and recognition process.

B. Approaches in On-line Handwriting Recognition

On-line handwriting recognition encompasses different approaches to accurately recognize and interpret handwritten text or symbols in real-time. Here we have explored some of the key approaches employed in the field, including statistical approaches, neural network-based approaches, etc.

a) Statistical Approaches

Statistical approaches have been widely used in on-line handwriting recognition, particularly in the early stages of research. These approaches involve the application of statistical models to capture the probabilistic relationships between the observed handwriting data and the underlying patterns.

i. Hidden Markov Models (HMMs): HMMs model the temporal dependencies in handwriting by representing the writing process as a sequence of hidden states corresponding to the underlying symbols. Kashi et. al. [18] successfully applied HMM for online handwritten signature verification. Thierry et. al. [19] applied HMM Online Handwritten Shape Recognition. HMM was also used by Bharath and Madhvanath [20] for online handwritten Tamil word recognition, Fink et. al. [21] for online Bangla word recognition and Rigoll et. al. [22] for Cursive Handwriting Recognition.

ii. b) Dynamic Time Warping (DTW): DTW is a distance-based method that measures the similarity between two-time series by aligning them in time. DTW has been applied to compare and recognize handwriting patterns by aligning pen strokes and calculating distance. Bahlmann et. al. [23] used Cluster Generative Statistical Dynamic Time Warping (CGSDTW) for online handwriting recognition which is writer-independent. Qiao and Yasuhara [24] used Affine Invariant DTW (AI-DTW) for online rotated handwritten data.

b) Neural Network-Based Approaches

Neural network-based approaches have the ability to learn complex patterns and capture the hierarchical structure of on-line handwriting data. Various types of neural networks have been employed for on-line handwriting recognition. Graves et. al. [25] used a recurrent neural network, Jaeger et. al. [26] used a multistate time delay neural network (MSTDNN) and Guyon et. al. [27] used Time Delay Neural Network (TDNN).

III. ON-LINE HANDWRITING RECOGNITION SYSTEMS

The recognition process involves several stages, including pre-processing, feature extraction, classification, and post-processing:

(i). Data capturing: This step captures the dynamic information of the handwriting process, such as pen movements, coordinates, pressure, timing, etc.

(ii). Pre-processing: During this step, captured data undergoes pre-processing to enhance its quality. Pre-processing steps may include noise filtering, normalization, resampling, etc. The irregular hand movements and inaccurate digitalization process are the causes of noise in handwritten strokes [8].

One of the widely used noise removal techniques is based on filtering algorithms, such as median filtering or low-pass filtering, to remove spurious points or smooth the stroke trajectories [11]. Normalization techniques, such as scaling and translation, are applied to align the data and make it invariant to size and position variations [28].

A few normalisation techniques include baseline drift correction [29], compensation for writing slant [30, 31], and script size adjustment [2].

(iii). Feature Extraction: In this stage, relevant features are extracted from the pre-processed data. Features can include geometric properties of pen strokes, acceleration, direction, or other temporal or spatial characteristics. These feature extraction methods aim to capture discriminative information while reducing the dimensionality of the data for efficient recognition algorithms.

Geometric features represent the spatial characteristics of handwriting strokes. Structural features focus on capturing the relationship between different parts of handwriting strokes, such as start and end points, and the sequence of stroke directions [11]. Other feature extraction techniques are Time-Based [8], Frequency-Based [8], high-level features such as loops, crossings, and cusps [17].

(iv). Classification and Recognition: The extracted features are used to classify and recognize the on-line handwritten input. Various machine learning techniques, such as statistical methods, neural networks, Hidden Markov Models (HMMs), SVM or hybrid models, are employed for classification and recognition tasks.

(v). Post processing: Post processing is often applied to improve the accuracy of on-line handwriting recognition. It involves incorporating linguistic knowledge, context, and grammar to enhance the recognition of words or phrases based on the surrounding context. Pitrelli and Perrone [32] used Confidence Modeling, Jianying and Brown [33] used N-best decoding, and Beigi et. al. [34] used dictionary-driven error-correction post-processor.

IV. CHALLENGES IN ON-LINE HANDWRITING RECOGNITION

The field of on-line handwriting recognition faces various challenges that researchers must address. Understanding and overcoming these challenges are crucial for improving the accuracy and robustness of on-line handwriting recognition systems. The system may need extra attention to handle instances involving crossing out words, or rewriting part of a word to make it more visible, or better looking, or sloppy handwriting etc. Few challenges are:

A. Variability in Writing Styles

One of the major challenges in on-line handwriting recognition is the inherent variability in individuals' writing styles. Handwriting can vary significantly among different writers in terms of stroke shapes, sizes, slants, and spacing.

B. Noise and Ambiguity in Data

On-line handwriting data often contain noise and ambiguity due to factors such as imperfect digitizing devices, overlapping strokes, or incomplete strokes. Noise and ambiguity can affect the accuracy of recognition algorithms by introducing errors or confusion during the recognition process.

C. Real-time Processing Requirements

On-line handwriting recognition systems are often required to operate in real-time scenarios. Achieving real-time processing while maintaining high recognition accuracy poses a significant technical challenge.

D. Multilingual Recognition

Multilingual on-line handwriting recognition involves recognizing handwriting from multiple languages with different character sets, writing styles, and linguistic characteristics. Accommodating the complexities and variations across multiple languages adds another layer of challenge to on-line handwriting recognition. Developing language-independent models require attention in multilingual on-line handwriting recognition.

E. User Adaptation

On-line handwriting recognition systems should be able to adapt to individual users' writing styles and preferences to improve recognition accuracy and user experience. User adaptation presents a challenge in terms of capturing and modelling individual variations, developing efficient adaptation techniques, and integrating them into the recognition pipeline. Personalization and user-centric design are crucial factors for enhancing the usability and effectiveness of on-line handwriting recognition systems

V. APPLICATIONS AND FUTURE DIRECTIONS

A. Applications of On-line Handwriting Recognition

On-line handwriting recognition has found diverse applications in various domains. Some of the key applications include:

1. Electronic signature verification

On-line handwriting recognition enables the development of electronic signature verification, where users can directly input text or commands using digital pen.

2. Interactive Handwriting-based Systems

On-line handwriting recognition has been integrated into interactive systems that support handwriting-based input for user interfaces, text editing, and text-based communication.

3. Note-Taking Appliances

Note-taking with respect to on-line handwriting refers to the process of digitally capturing handwritten notes using a device such as a tablet or a touchscreen. It allows individuals to write and draw on a digital platform, replicating the experience of traditional pen and paper note-taking. Note-taking application provides access to handwritten notes to a workgroup and can be shared with other group members.

4. Interactive Whiteboard

Online handwriting recognition can be applied to convert handwritten content from whiteboards or digital boards into editable text. This allows for better retention and organization of whiteboard discussions, making it easier to distribute the information. Researchers [35, 36, 37] worked on concept of whiteboard.

B. Future Directions

The advancements in on-line handwriting recognition continue to evolve, and several directions offer potential for future research and development:

1. Integration of Machine Learning Techniques

With the increasing availability of large-scale handwriting datasets, the integration of machine learning techniques, such as deep learning models, can further enhance the performance of on-line handwriting recognition systems. Deep neural networks, recurrent neural networks, and attention mechanisms have shown promise in improving recognition accuracy [38].

2. User-Adaptive Systems

Future on-line handwriting recognition systems can focus on user adaptation, where the system can dynamically adapt to individual users' writing styles, preferences, and variations.

3. Multi-Modal Interaction

Integrating on-line handwriting recognition with other modalities, such as speech and gesture recognition, can enable multi-modal interaction and enhance the usability of interactive systems.

VI. CONCLUSION

On-line handwriting recognition is a dynamic field and advancements have enabled various applications. An overview of the advancements and challenges in online handwriting recognition is provided in this study. It emphasis on the fundamental ideas and uses. It also discusses the substantial difficulties faced by academics in this area and suggests possible paths for future work in online handwriting recognition.

REFERENCES

[1]. Sivaramakrishnan, K. R., and Chiranjib Bhattacharyya. "Time series classification for online tamil handwritten character recognition–A kernel based approach." In Neural Information Processing: 11th International Conference, ICONIP 2004, Calcutta, India, November 22-25, 2004. Proceedings 11, pp. 800-805. Springer Berlin Heidelberg, 2004.

[2]. Nouboud, Fathallah, and Rejean Plamondon. "On-line recognition of handprinted characters: Survey and beta tests." Pattern Recognition 23, no. 9 (1990): 1031-1044.

[3]. Graves, Alex, Marcus Liwicki, Santiago Fernandez, Roman Bertolami, Horst Bunke, and Jurgen Schmidhuber. "A novel connectionist system for unconstrained handwriting recognition." IEEE transactions on pattern analysis and machine intelligence 31, no. 5 (2008): 855-868.

[4]. Vapnik, N.V., "The Nature of Statistical Learning Theory", Second Edition, Springer,1999.

[5]. Bothe, Sebastian, Thomas Gärtner, and Stefan Wrobel. "On-line handwriting recognition with parallelized machine learning algorithms." In KI 2010: Advances in Artificial Intelligence: 33rd Annual German Conference on AI, Karlsruhe, Germany, Proceedings 33, pp. 82-90. Springer Berlin Heidelberg, 2010.

[6]. Pavlidis, Ioannis, Rahul Singh, and Nikolaos P. Papanikolopoulos. "On-line handwriting recognition using physics-based shape metamorphosis." Pattern Recognition 31, no. 11 (1998): 1589-1600.

[7]. T. Mondal, U. Bhattacharya, S. K. Parui, K. Das and D. Mandalapu, "On-line Handwriting Recognition of Indian Scripts - The First Benchmark," 2010 12th International Conference on Frontiers in Handwriting Recognition, Kolkata, India, 2010, pp. 200-205

[8]. Toselli, Alejandro H., Moises Pastor, and Enrique Vidal. "On-line handwriting recognition system for tamil handwritten characters." In Pattern Recognition and Image Analysis: Third Iberian Conference, IbPRIA 2007, Girona, Spain, June 6-8, 2007, Proceedings, Part I 3, pp. 370-377. Springer Berlin Heidelberg, 2007.

[9]. Tappert, Charles C., Ching Y. Suen, and T. Wakahara."On-line handwriting recognition: A survey." IBM Thomas J. Watson Research Division, 1988.

[10]. Tappert, Charles C., Ching Y. Suen, and Toru Wakahara. "The state of the art in online handwriting recognition." IEEE Transactions on pattern analysis and machine intelligence 12, no. 8 (1990): 787-808.

[11]. Plamondon, Réjean, and Sargur N. Srihari. "Online and off-line handwriting recognition: a comprehensive survey." IEEE Transactions on pattern analysis and machine intelligence 22, no. 1 (2000): 63-84.

[12]. J.F. Heabert, M. Parizeau, and N. Ghazzali, "Learning to Segment Cursive Words Using Isolated Characters," Vision Interface '99, (1999): 33-40, Trois-Rivieares, France

[13]. J. Mackowiak, L.R.B. Schomaker, and L. Vuurpijl, "Semi-Automatic Determination of Allograph Duration and Position in On-Line Handwriting Words Based on the Expected Number of Strokes," Progress in Handwriting Recognition. A.C. Downton and S. Impedovo, eds., London: World Scientific, 1997.

[14]. A. Hennig, N. Sherkat, and R.J. Whithrow, "Recognizing Letters in On-Line Handwriting Using Hierarchical Fuzzy Inference," In Proceedings of the Fourth International Conference on Document Analysis and Recognition, vol. 2, pp. 936-940. IEEE, 1997

[15]. R. Plamondon, "A Model-Based Segmentation Framework for Computer Processing of Handwriting," Proc. 11th Int'l Conf. Pattern Recognition,(1992),. 303-307, The Hague, Netherlands

[16]. Anquetil, Eric, and Helene Bouchereau. "Integration of an on-line handwriting recognition system in a smart phone device." In 2002 International Conference on Pattern Recognition, vol. 3, pp. 192-195. IEEE, 2002.

[17]. Hu, Jianying, Amy S. Rosenthal, and Michael K. Brown. "Combining high-level features with sequential local features for on-line handwriting recognition." In Image Analysis and Processing: 9th International Conference, ICIAP'97 Florence, Italy, September 17–19, 1997 Proceedings, Volume II 9, pp. 647-654. Springer Berlin Heidelberg, 1997.

[18]. Kashi, Ramanujan, Jianying Hu, W. L. Nelson, and William Turin. "A Hidden Markov Model approach to online handwritten signature verification." International Journal on Document Analysis and Recognition 1, no. 2 (1998): 102-109.

[19]. Artieres, Thierry, Sanparith Marukatat, and Patrick Gallinari. "Online handwritten shape recognition using segmental hidden markov models." IEEE transactions on pattern analysis and machine intelligence 29, no. 2 (2007): 205-217.

[20]. Bharath, A., and Sriganesh Madhvanath. "Hidden Markov models for online handwritten Tamil word recognition." In Ninth International Conference on Document Analysis and Recognition (ICDAR 2007), vol. 1, pp. 506-510. IEEE, 2007.

[21]. Fink, Gernot A., Szilard Vajda, Ujjwal Bhattacharya, Swapan K. Parui, and Bidyut B. Chaudhuri. "Online Bangla word recognition using sub-stroke level features and hidden Markov models." In 2010 12th international conference on frontiers in handwriting recognition, pp. 393-398. IEEE, 2010.

[22]. Rigoll, Gerhard, Andreas Kosmala, and Daniel Willett. "A new hybrid approach to large vocabulary cursive handwriting recognition." In Proceedings. Fourteenth International Conference on Pattern Recognition, vol. 2, pp. 1512-1514. IEEE, 1998.

[23]. Bahlmann, Claus, and Hans Burkhardt. "The writer independent online handwriting recognition system frog on hand and cluster generative statistical dynamic time warping." IEEE Transactions on Pattern Analysis and Machine Intelligence 26, no. 3 (2004): 299-310.

[24]. Qiao, Yu, and Makoto Yasuhara. "Affine invariant dynamic time warping and its application to online rotated handwriting recognition." In 18th International Conference on Pattern Recognition (ICPR'06), vol. 2, pp. 905-908. IEEE, 2006.

[25]. Graves, Alex, Marcus Liwicki, Horst Bunke, Jürgen Schmidhuber, and Santiago Fernandez. "Unconstrained on-line handwriting recognition with recurrent neural networks." Advances in neural information processing systems 20 (2007).

[26]. Jaeger, Stefan, Stefan Manke, Jürgen Reichert, and Alex Waibel. "Online handwriting recognition: the NPen++ recognizer." International Journal on Document Analysis and Recognition 3 (2001): 169-180.

[27]. Guyon, Isabelle, Paul Albrecht, Yann Le Cun, J. Denker, and Wayne Hubbard. "Design of a neural network character recognizer for a touch terminal." Pattern recognition 24, no. 2 (1991): 105-119.

[28]. Huang, Bing Quan, Y. B. Zhang, and Mohand Tahar Kechadi. "Preprocessing techniques for online handwriting recognition." In Seventh International Conference on Intelligent Systems Design and Applications (ISDA 2007), pp. 793-800. IEEE

[29]. M.K. Brown and S. Ganapathy, "Preprocessing Techniques for Cursive Script Word Recognition," Pattern Recognition, vol. 16, (1983):447-458

[30]. D.J. Burr, "Designing a Handwriting Reader," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 5, (1983):554-559, 1983.

[31]. F.J. Maarse and A.J.W.M. Thomassen, "Produced and Perceived Writing Slant: Difference Between Up and Down Strokes," Acta Psychologica, vol. 54, (1983):131-147

[32]. Pitrelli, John F., and Michael P. Perrone. "Confidence modeling for verification post-processing for handwriting recognition." In Proceedings Eighth International Workshop on Frontiers in Handwriting Recognition, pp. 30-35. IEEE, 2002.

[33]. Hu, Jianying, and Michael K. Brown. "On-line handwriting recognition with constrained n-best decoding." In Proceedings of 13th International Conference on Pattern Recognition, vol. 3, pp. 23-27. IEEE, 1996.

[34]. Beigi, Homayoon SM, T. Fujisaki, W. Modlin, and K. Wenstrup. "A Post-Processing Error-Correction Scheme Using a Dictionary for On-Line Boxed and Runon Handwriting Recognition,"." In Proc. of Canadian Conference on Electrical and Computer Engineering, Toronto, Canada, vol. 2, pp. 5-1. 1992.

[35]. Liwicki, Marcus, and Horst Bunke. "IAM-OnDB-an on-line English sentence database acquired from handwritten text on a whiteboard." In Eighth International Conference on Document Analysis and Recognition (ICDAR'05), pp. 956-961. IEEE, 2005.

[36]. Nakagawa, Masaki, and Motoki Onuma. "Online handwritten Japanese text recognition free from constrains on line direction and character orientation." In Seventh International Conference on Document Analysis and Recognition, 2003. Proceedings., pp. 519-523. IEEE, 2003

[37]. Schlapbach, Andreas, Marcus Liwicki, and Horst Bunke. "A writer identification system for on-line whiteboard data." Pattern recognition 41, no. 7 (2008): 2381-2397.

[38]. Graves, Alex, Marcus Liwicki, Santiago Fernandez, Roman Bertolami, Horst Bunke, and Jurgen Schmidhuber. "A novel connectionist system for unconstrained handwriting recognition." IEEE transactions on pattern analysis and machine intelligence 31, no. 5 (2009): 855-868.