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A Study of Approaches for Handwriting Recognition and Generation

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Abstract: Image processing, data analytics and artificial intelligence methodologies for handwriting recognition and generation are overviewed. Different solutions with off-line and on-line handwriting samples are studied. Generative models for handwriting are analysed and the possibilities are assayed. The accuracy of these approaches is compared and the current state of research for these problem is considered.

Keywords: *artificial intelligence, markov models, genetic algorithm, handwriting, recognition, generation, off-line, on-line, machine learning, neural networks, information retrieval, document analysis*

I. Introduction

Handwriting recognition is something that is of great interest, both academically and commercially. It is one of the oldest research focuses in information retrieval and document analysis and recognition. Handwriting recognition has two main subcategories; on-line handwriting involves the automatic conversion of text as it is written on a PDA or a digitizer with a special 'ink'. On-line handwriting is the more relatively popular and well used mechanism. Off-line handwriting is harder as it involves handwriting recognition from static handwriting samples. Machine generated text can be recognised with Optical Character Recognition (OCR) while Intelligent Character Recognition (ICR) and Intelligent Word Recognition (IWR) are used for user generated text or handwriting. Commercial note-taking applications provide OCR. They do not work well with handwriting samples i.e off-line handwriting recognition as these samples lack the uniformity and low deviation present in machine generated text, which makes OCR possible.

The problem with off-line handwriting recognition is the lack of continuous input or the inability to follow the user's input as he/she writes. On-line handwriting is more popular mainly owing to the fact that it has a continuous stream of input from the stylus or pen that it can compute to recognise the text being written. Off-line handwriting has many more applications as there is a huge amount of handwritten data that has not been recognised. One of the applications of such a recognition system can be in crime, to detect and match incriminating documents to a single individual. This idea of recognising and matching handwritten text can be extended to history, wherein various historical documents can also be checked for their source in this way. Handwriting recognition using neural networks has been a field with a lot of interest. Neural networks have become a major part of machine learning and are the main catalyst in deep learning, providing the structure for a machine to learn and apply that knowledge in the same way that a human can. They have paved the way for new possibilities in off-line handwriting recognition and it is quite obvious that a commercial handwriting recognition and generation system would prove very useful in various real world problems.

This paper studies the various approaches and techniques used to deal with handwriting recognition on off-line and on-line samples and handwriting generation. An overview of systems is given and the different steps and parameters involved in building these systems is considered. In section II, off-line handwriting solutions over the course of the last few decades are studied. More recent solutions with on-line handwriting are overviewed in section III. With the advent of bioinformatics and artificial intelligence, more accurate models for handwriting recognition and handwriting generation have been formulated. Current generative models and future possibilities are explored in sections IV and V. The accuracy of both recognition and generative models are compared. The current state of research and future possibilities are also analysed.

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II. EARLY ADVANCEMENTS IN HANDWRITING RECOGNITION

Handwriting recognition has been a focus of research in information retrieval for the past four decades. The presence of large amounts of information in handwritten forms is the major cause for this. There was a need for accurate models that could extract information from these documents while offsetting the accuracy error caused by their stochastic nature. Early attempts focused on using statistics to solve this problem. Off-line handwriting samples were widely used as data for these approaches.

A. Statistical Models

M. Plamondon and N. Srihari [36] and A. L. Koerich et al. [27] are early surveys on off-line handwriting approaches. The majority of these proposals used statistical models to perform lexical recognition. N. Bouadjenek et al. [3] focuses on attempts at recognising machine generated characters, namely OCR. Recognition of words with large lexicons and line separation has been achieved, mostly in structured environments [7], [6]. Early research done in language models is analysed. Grammatically correct paths and word productions are used to construct a model with an accuracy of 80%, which can possibly be increased to 95% [42]. The difficulty in reliability as number of words increase is offset by the proposal of early models like the maximum entropy models [38] and N-Gram class models [25]. J. Cai and Z. Liu [4] deals with the scale of the problem at hand, analysing how large vocabularies can cause inaccuracies in recognition. It states that accurate recognition is not possible without the use of language models, but the trade-off would be complexities and high computational costs. A fast-search strategy is benchmarked and compared on various hardware.

Markov models and hidden Markov models have been used extensively for handwriting recognition. One of the first uses of the Markov model for recognition [22] uses semantic constructs and probabilistic descriptions to differentiate between feature strings and semantic classes. A modification of the Viterbi algorithm [45] is shown to reduce the number of words required for a match. A detailed study of Markov-chain models and hidden Markov models for offline handwriting recognition [37] overviews more complex models [4], [12] like random Markov field models (MRF) and conditional random field models (CRF) are studied as well. It states the importance of Gaussian covariances, number of states and type of smoothing applied in the model.

B. Structural Models

Towards the end of the decade, structural, rule-based and classification models were on the rise. Statistical classification is used to perform handwriting recognition [35] and it deviates from the usual off-line data for testing by using on-line samples. A fuzzy syntactic model to recognise characters from cursive scripts i.e non-machine generated or non-block characters [34] deals with the additional complexities of trailing characters and common lines.

C. Knowledge Driven Models

Although recent advancements have achieved great results with the use of machine learning, knowledge-driven models and soft computing, early attempts with unsupervised learning

[19] and data driven models [20] were not satisfactory. Unsupervised learning, where the machine is provided with unlabelled offline handwriting samples and left to derive its own inferences could not segment words [19]. Hierarchical fuzzy inference, a data driven or knowledge driven approach to segment words [20] had the same problem. The inability to segment cursive letters in words led to plain results in both cases. Recent advancements in soft computing, knowledge reasoning, machine learning and deep learning has led to researchers revisiting these models and achieving highly accurate recognition and generation.

III. RECENT TRENDS IN RECOGNITION

Post 2000, there has been a shift in approaches used for on-line and off-line handwriting recognition. More on-line handwriting data was available, through datasets like IAM [31], while datasets in other languages like KHATT [33] were also constructed. Statistical methods are still present and used for feature extraction and recognition [32]. It performs a comparative study with statistical classifiers, neural networks, pattern matching, etc. The statistical classifiers did not perform as well as the other approaches. A fuzzy integral [3] provided a 4% increase in accuracy over combinational rules. It produced higher accuracy on both IAM [31] and KHATT datasets.

The use of global features, Hu's moment invariants, skew, Zernike moments, projections, profile features, background features, etc produced a high accuracy of 96% [14]. Although SVM was used as the classifier, statistical methods were used to extract the features. The high accuracy is possible because of the use of a dataset of digits. The same result cannot be translated to handwriting or cursive scripts.

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Another novel approach [5] uses the Levenshtein distance metric to perform online handwriting recognition. Angular displacement between sample points with assigned integral weights is used to calculate a similarity metric. It produced an accuracy of upto 86% on indigenous languages. The use of artificial intelligences, bioinformatics and applied soft computing methodologies has achieved accuracies of above 90% while dealing with the complexities of line recognition, space between characters, cursive writing, etc. These methods have been applied successfully in conjunction with more traditional statistical approaches.

G. Katiyar and S. Mehfuz [24] use a simpler Multi Layer Perceptron Neural Network (MLPNN) and Genetic Algorithms (GA) for hybrid feature selection and extraction. Training and testing is done on off-line data. An accuracy of 94.65% is achieved. However, its performance beyond the dataset is not known. Additionally, the model is not experimented on with on-line samples. Conversely, the hybrid feature selection and the MLPNN classifier produced an approximate improvement of 50% on other approaches.

A. *Support Vector Machines*

Support Vector Machines (SVMs) are based on statistical learning and have been widely used for single-class and multi-class classification tasks. C. Bahlmann et al. [1] describes SVMs, discriminative and generative models and examples of two class and multi class problems. K. Sivaramakrishnan et al. [41] defines kernels for time-series classifications. These put forward good ideas to be used in recognition tasks. The possibilities of SVMs for large datasets and high performance with sparse coding is explore [28], [9].

HMMs with SVMs [21] have low discriminatory abilities with regard to pattern recognition. SVMs cannot be used for variable length samples. The paper proposes an idea that puts the merits of HMMs and SVMs to good use. The UNIPEN [18] on-line database is used for training and testing. Digit accuracy of 97.48% and lower and upper character accuracy of 91.74% and 91.99% respectively were achieved. An earlier work [24] was an influence as it proposes another hybrid system, with Multi Layer Perceptron (MLP) and SVMs. The MLP decision and the SVMs' decision is taken into account. It states that a theoretical accuracy of 91% is possible. SVMs caused a huge increase in accuracy and performance in on-line and off-line recognition. However, they fell short of dealing with complex handwritten sentences, very large vocabulary and reproducing high accuracy measures for handwriting samples.

B. *Neural Networks*

Deep Belief Neural Networks (DBNs) have been used for handwriting recognition [23], [11], [39] producing great results. Recent research has focused on the the use of Recurrent Neural Networks (RNNs) and extensions like LSTMs [16], [13], [44], [15] which can also be used for generation.

G. Hu et al. [23] uses DBNs with the dropout method; units of hidden or visible layers are 'dropped' during training. This is useful for avoiding overfitting or when the training data is not big enough. The proposed dropout method is an improvement, with the use of probability statistics. Indigenous offline digit recognition is done with various neural network models like DBN, Convolutional Neural Networks (CNN) with dropout, normal CNNs, CNNs with Gaussian filters, etc. A specific method, CNNs with Gabor filters [46], achieved a recognition rate of 98.78% for a dataset in Bengali [8]. The increase in accuracy over DBNs is nominal, however, considering the performance trade-off in using multiple filters. Like other research previously analysed [24], [14], the dataset is again confined to 10 classes, or 10 digits to be recognised. A larger vocabulary would cause unknown levels of degradation with regard to accuracy. Arabic handwritten character recognition is also done with DBNs [11]. It trains and tests a DBN on the HACDB [29] off-line Arabic character dataset. Although it reaches an accuracy of 97.9%, it cannot deal with variable input length, as supported by it's 41% error rate on the ADAB [26] on-line database. The bidirectional nature of Bidirectional Long Short Term Memory (BLSTM) RNNs can address this problem. The use of DBNs along with RNNs has been observed [39] to produce good results. This approach uses RNNs' hypotheses to obtain character boundaries through word alignments. DBNs are then used to verify the alignments and produce probabilities. An MLP rescoring method is used on the Rimes dataset [17] for comparison with the proposed method. The DBN and MLP approaches produce an accuracy of 97.41% for the Top 5 word hypotheses, while DBN outperforms MLP for N-word hypotheses of Top 1, Top 2, Top 3 and 4.

Their ability to deal effectively with sequences and exhibit temporal behaviour makes RNNs a good choice for handwriting recognition. Recent research has also produced approaches that can perform generation [16]. Additionally, it addresses the low performance of early work when dealing with continuous handwriting. The use of deep learning techniques like BLSTM NNs has made this possible. Using BLSTM NNs to train and test handwriting recognition on the

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IAM [31] dataset has led to insightful observations [13]. The BLSTM nature of the network deals with long-term dependencies. One of the main takeaways is the superior reduction of error rate by using recurrent layers over feed-forward Rectified Linear Units (ReLUs).

Samples	Proposal	Accuracy (%)		Dataset
		Digits	Characters	
On-line	Generation with RNNs [16]	-	71.50[a]	IAM-OnDB [31]
	Hybrid of SVM and HMM [21]	97.48	91.99	UNIPEN [18]
	BLSTM RNNs [13]	-	72.89	IAM-OnDB [31]
	Levenshtein Distance Metric [5]	-	86.00	Private
Off-line	Hybrid of SVM and NN [24]	-	91.00	Private
	CNN with Gabor filters [46]	98.78	-	Bangla Digits [8]
	Arabic with DBNs [11]		97.90 59.00	HACDB [29] ADAB [26]
	DBNs with RNN rescoring [39]	-	97.41	RIMES [17]
	RNN classifiers on segmented text [44]	-	93.32	Private
	Multidimensional RNNs	96.75	-	MNIST [30]
	BLSTM with Trigrams [47]	-	84.70	Private
	MLPNN and GA [24]	94.65	-	MNIST [30]

TABLE I: COMPARISON OF APPROACHES AND ACCURACY FOR PAPERS POST 2000

Another approach is to use different features with a RNN model [44]. The geometric features and the Histogram of Oriented Gradient (HOG) feature are used. Geometric features consist of the number of text pixels, center of

gravity of a group of pixels, orientation of uppermost and lowermost pixels, to name a few. An accuracy of 93.32% is achieved with combined features, while individually, geometric features with a RNN classifier produces 84.82% and HOG feature with RNN classifier produces 91.00%. There is a possibility for different classifiers to be used and the time of decoding to be reduced.

Other novel approaches include using multidimensional RNNs and additional techniques like n-grams [25], [47]. The use of multidimensional RNNs negates the use of two separate models for preprocessing and prediction [15]. On off-line datasets, the model takes in raw pixels as inputs, trains and tests against the dataset and recognises handwriting. An accuracy of 96.75% was achieved for the Top 10 word hypotheses. This is superior to the performance of HMMs on the same dataset. N-grams like bigrams and trigrams are used along with RNNs as well [47]. Use of n-grams partially offsets the lack of sufficient data. Two recognizers are used on the training data, which is split into trigrams. A modified token passing algorithm and a BLSTM RNN is used for predictions. The method has not, however, been tasted on text line data.

Through varying neural network structures and soft computing techniques, there has been a paradigm shift in different fields of computer science. In handwriting recognition, deep learning techniques has allowed for highly accurate results that deal with variable input length, continuous input, long-term dependencies and showcase consistent performance across heterogeneous data.

IV. Possibilities Of Generative Models

Handwriting recognition on off-line and on-line data is still a very active research area, pursued closely by document analysis and prediction researchers. Few researchers have RNNs, especially with LSTMs, have been widely used for generation of data that was previously confined to human creation, like music and speech. Various commercial personal assistants like Google's Assistant and Apple's Siri use these techniques for speech generation. Music composition was done with RNNs [10], which outlined the surprising performance of these models. Text generation [45] was also done as early as 2011.
One of the well-known articles that look at handwriting generation [16] has outlined a simple model to use on-

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line handwriting data to first recognise, and then produce nearly alike handwriting samples from text. Demonstrated on the IAM [30] dataset, the model uses stochastic gradient descent and biased sampling for recognition and generation. With a probability bias of 1, highly accurate samples are produced.

V. Approaches Used And Future Work

Over the course of two decades, there have been varying approaches to the problem of handwriting recognition. There have been differing results and no definite forerunner with regard to accuracy. Table 1 lists a few of the recent work in this field, while outlining the accuracy and the methods used. It is safe to say that the future of document analysis, recognition and possibly, generation, lies in the harnessing of neural networks and new technology like capsule networks [40]. These methods have dealt with complexities and dependencies like variable text length, large vocabulary size, insufficient training data, continuous sequences, long-term dependencies and more. Recent work does indeed point to more researchers adopting these approaches for their solutions.

VI. Conclusion

This paper has briefly listed some of the influential work and approaches taken for handwriting recognition and generation in the past two decades. Earlier models like statistical, structural and knowledge driven models were listed. The use of modern knowledge driven models has possibly not been explored to its fullest extent. However, the performance of SVMs and NNs for this problem has pushed these methods to the forefront of document analysis and recognition for the near future. Data driven generative models [16], [10], [43] have been made possible with the ability of NNs to model long term dependencies and variable lengths effectively, and there's a good possibility of more work in handwriting generation in the coming future.

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