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A Possibility for Handwriting Trajectory Reconstruction with Deep Learning

Yu Han Lin[1], **Erikson F. de Morais**[1], **Simone B. K. Aires**[1]

[1]Departamento Acadêmico de Informática – Universidade Tecnológica Federal do Paraná (UTFPR)
Av Monteiro Lobato s/n, Km 04 – Ponta Grossa – PR – Brasil

nilyuhan@gmail.com, {emorais,sbkaminski}@utfpr.edu.br

Abstract. *Studies on handwriting trajectory recovery have gained space in the offline recognition of manuscript researches. The reason is the use of online recognition resources, creating techniques to simulate the writing of the handwritten word and inserting the simulated coordinates of the pixels in online handwriting recognition systems. The present work aims to present the possibility to perform the reconstruction of the trajectory of handwritten characters using an existing deep learning architecture. This reconstruction involves recovery of the coordinate sequence of the trajectory of the character and, if needed, the retrieval of missing parts of the characters. First of all, the state of art about handwriting trajectory is presented. Experiments of handwriting characters trajectory recovery using deep learning model is performed and shows that the actual deep models of handwriting trajectory recovery architecture can recover some missing parts of the characters. In the end, presents the conclusion of the work.*

Keywords: Deep Learning, Handwriting Trajectory Recovery, Handwriting Reconstruction, Image Recovery

1. Introduction

The ability to transmit a message or idea through specific handwriting language is unique to each person. Handwriting recognition consists to transform the language in graphics marks into digital signals [Plamondon and Srihari 2000].

The handwriting analysis and recognition can be classified into two categories: Offline and Online. The online recognition is to transcript the handwriting from some special input device, which provides dynamic and temporal information, like the sequence coordinate points and pen pressure; and the offline recognition is the process that extracts and identifies the handwriting from static handwriting images [Plamondon and Srihari 2000].

By the limited information of offline images, offline recognition is performed with less accuracy than online recognition [Zhang et al. 2017]. Based on that limitation, handwriting trajectory recovery (HTR) system is developed, recovering the temporal order of the handwriting strokes from statics images.

The main task of HTR is to find an oriented path of the strokes of the image similar to that done during the writing operation. With the dynamics information recovered, handwriting images that have similar geometric forms can be distinguished [Noubigh and Kherallah 2017]. The example of those situations is shown in Figure 1, in which both image numbers (four and nine) have similarities in their geometric shapes.

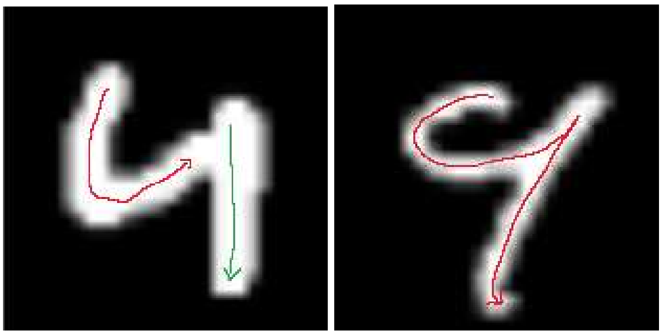


Figure 1. The example of number four (on the left) and nine (on the right), which is written with two and one stroke, respectively.

To recover the online data, [KumarBhunia et al. 2018] uses the recent successful deep learning model to propose a novel technique for HTR by using a merged of Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) to predict coordinates points from a given offline character.

Following the idea of recovering data, the reconstruction handwriting process also can be explored. This paper explores the model proposed by [KumarBhunia et al. 2018] to perform the reconstruction of handwriting trajectory. In this work, the reconstruction consists of the recovering of handwriting trajectory from the character image and also the retrieve of missing parts of those images when it went through (e.g., natural causes of disintegration). To simulate the disintegration of an offline image, we artificially remove some parts of the image to perform the reconstruction process.

The organization of this paper is described as follows. Firstly, we present a bibliography of a trajectory recovery based handwriting recognition system. Then, the methodology and implementation of the experiment are presented in section 3. Experiment results and analysis are discussed in section 4. Section 5 brings up the conclusion and future works.

2. Related Work

The works [Noubigh and Kherallah 2017] and [Nguyen and Blumenstein 2010] have reported that the techniques have adhered to the hypothesis of [Rousseau et al. 2006] trying to recovery dynamic information from static offline character images.

The two major approaches found in the literature to recovery handwriting trajectory are heuristic rules algorithm to find the optimal graph path and artificial intelligence or machine learning-based algorithm. The first consists of preprocessing the character offline image using a technique called skeletonization, then convert the character skeleton into a graph and develop an algorithm to find the optimal graph path. The second consists of apply artificial intelligence or deep learning to approximate the probability of the trained model to reproduce the handwriting.

The work present by [Sharma 2013] recover the handwriting trajectory by using two algorithms that use the code chain from a skeleton character image. In the sequence [Sharma 2015] use the dynamic features from the previous work [Sharma 2013] and the statics features from static handwriting images to perform the handwriting character recognition, showing that the combination of both types of features can achieve better results than using only one type of feature.

By using a genetic algorithm, [Elbaati et al. 2009] optimizes the best trajectory from segments obtained from a character skeleton image. Dynamic information is restored from the stroke chronology and is used to perform the Arabic handwriting recognition.

The deep learning was a recent technique applied by [KumarBhunia et al. 2018]. The principle is using the feature extraction from convolutional neural networks to extract the feature sequence from the offline handwriting image, then use the encoder-decoder LSTM in seq2seq model to compute the feature codified by the convolutional neural network and produce the final coordinates sequence.

3. Methodology

In this section, we detail the offline to online data translation process, introducing the dataset and the handwriting reconstruction process. The deep neural network is from the work of [KumarBhunia et al. 2018], which is used as a start point experiment to perform the handwriting reconstruction and recover missing parts of the characters.

3.1. Reconstruction Process

With the predicted points, we can perform the possibility of reconstruction process. To check if the network can recover some missing parts, four regions are delimited to be withdrawn: upper left, upper right, down left and downright. The Figure 2 shows the delimited region from a offline Telugu character.

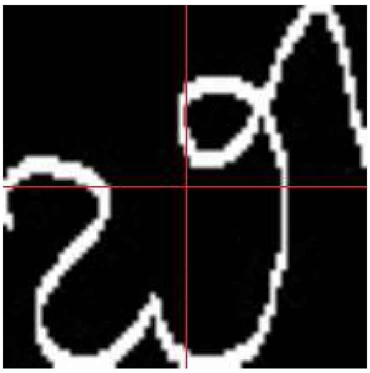


Figure 2. Regions delimited to be withdrawn.

This occlusion test was performed in samples in which the sequence coordinate points were predicted correctly by the network.

3.2. Implementation Details

The length of each layer input and output of the CNN is described in Table 1.

Table 1. The Input and Output of each layer from CNN

# layer	*Input*	*Output*
1	4096	64
2	64	128
3	128	256
4 - 8	256	256

The pooling method 1x2 [Shi et al.] is adopted and is applied after the layers 1, 2, 4, 5 and 7. Batch normalization is applied after 3^{th}, 6^{th} and 8^{th} convolutional layer, speeding up the training process. ReLu activation function is applied after the layers 3, 6 and 8.

The two bidirectional LSTM with 256 cells each are stacked to have higher abstraction ability [KumarBhunia et al. 2018]. To obtain each point from the decoder network at a particular time-step t, a fully connected layer is used (with 256 input length and 2 output), and the previous time-step is the input at the next time-step of the decoder.

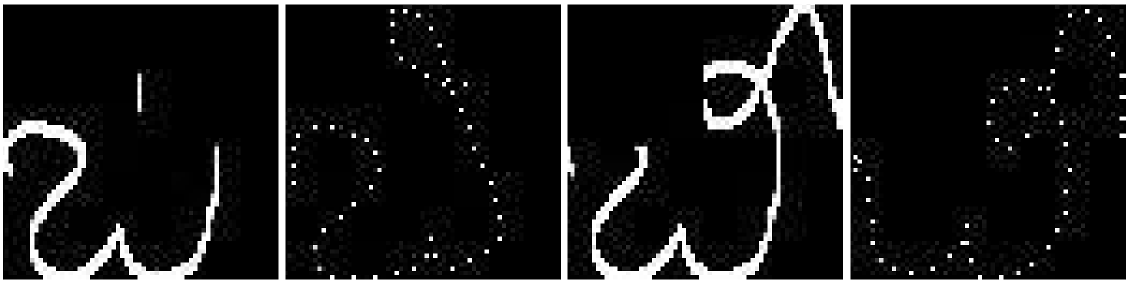
4. Experiments and Results

For our experiment, [KumarBhunia et al. 2018] provides a dataset with 7875 samples of Telugu script. It is a type of Indic script which contains the character level of both online and offline data. We train our model with those samples to predict the coordinate points of the characters.

The predicted coordinate points are translated to the nearest point on the skeleton of the offline image as a post-processing step. For the characters that the shape format which achieved a satisfactory result, the occlusion test was performed as described previously. The Figure 3 shown the offline images used to check if the network can reconstruct the shape of the original character when it's provided an offline character with missing parts. For each sample showed in Figure 3, the original image is the one on the left (with a full traced path of the Telugu character) and the predicted coordinates image is on the right.

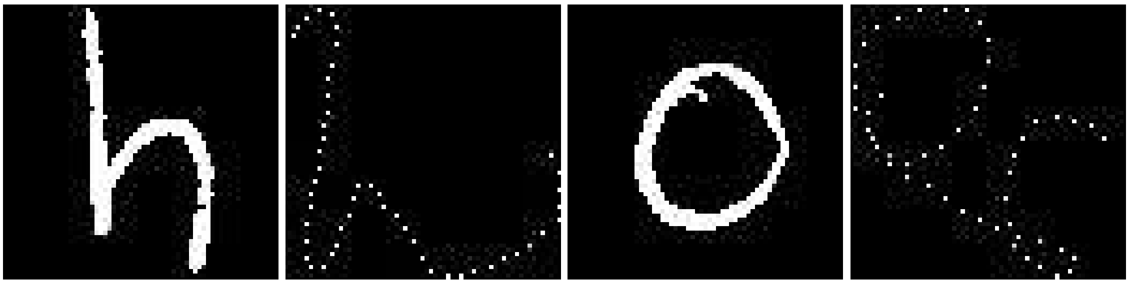
Figure 3b shows that the network can recover partially the missing part of the offline character. The Figure 3d also shows the network behavior to recover the curve from the missing upper left region, producing a little curve at the same region in the output.

As part of the experiments, some samples of Latin character from IRONOFF dataset is used to check the behavior of network when it is trained with Telugu characters and fed with Latin characters, showed in Figure. 4. This process can provide an initial experiment for the technique called Transfer Learning [Pan and Yang 2009].



(a) (b) (c) (d)

Figure 3. Reconstruction of offline characters with online coordinates data translated to offline.



(a) (b) (c) (d)

Figure 4. Reconstruction of offline Latin characters with online coordinates data translated to offline when the network was trained with Telugu characters.

It is to be expected that the network will not recover Latin characters. However, the Figure 4b shows the output of network seems similar from the input Figure 4a. In the case shown by Figure 4d, the network can reproduce the complete loop from the original character Figure 4c, but output some additional parts. The network could interpret that the character has some missing part, compared to some Telugu character learned. Those examples show the capability of the network to generalize even be trained with another dataset of another language.

5. Conclusion and Future Works

In this work, experiments using deep learning aiming to reconstruct handwriting trajectory was performed. Those experiments include the use of the framework proposed by [KumarBhunia et al. 2018] and have show a possibility for handwriting trajectory reconstruction when the handwriting character image has hidden parts.

Even without a large amount of data to perform the training, the deep neural network could partially reconstruct a few handwriting images, showing that there are indications that deep neural networks may have the ability to predict pixels in regions that have been removed or lost.

That prediction ability brings up possibilities to continue this research. In the future works, we will train the network with Latin characters from IRONOFF database. Transfer Learning from a Telugu trained network to train the Latin network will be on the line. Also, use the zoning proposed by [Freitas et al. 2007] to perform the withdraw regions, so we can have a zoning mechanism guide to simulate missing parts of an offline character image.

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