Handwritten signatures can be employed as a sign of confirmation in a wide variety of documents, namely, bank checks, identification documents and a variety of business certificates and contracts. Since those documents present complex backgrounds, the automatic extraction of handwritten signature from documents remains as an open task in the Offline Signature Verification field. In this paper we propose a method for the stroke-based extraction of signatures from document images. The approach is based on a Fully Convolutional Network trained to learn an end-to-end nonlinear mapping to extract the signatures from documents. Due to the lack of publicly available datasets containing the ground truth of signatures on the stroke level [1], we trained and evaluated our model on a dataset we created synthetically from real documents. It contains the stroke-based ground truth of signatures in a variety of documents with complex backgrounds. As a contribution of this work, the dataset will be made publicly available. Our method shows promising results on the test set, 89.8% recall and 66.9% precision.

PROPOSED SYSTEM

In order to create a signature segmentation method without using any prior knowledge of the layout structure of the documents, we consider the signature segmentation problem as a pixel classification task and use a Fully Convolutional Network (FCN) inspired in the Long et al. [2] and Ronneberger et al. [3] models. Our FCN architecture is presented in Fig. 1.

As a preprocessing step, we normalize the images to the largest image size, by padding the images with white background. Then, we center the manuscript in a canvas with size of the largest sample size in the dataset, aligning the center of mass of the sample to the center of the image. Then, we rescale the images, using a bilinear interpolation, to 512x512 pixels, maintaining the aspect ratio of the original sample. Finally, we inverted the images so that the white background corresponded to pixel intensity 0, and normalized the input to our FCN by dividing each pixel by the standard deviation of all pixel intensities.

We initialized the weights of the model using the technique proposed by Glorot and Bengio, and the biases to 0. We trained the model with Adam optimizer to minimize the dice coefficient loss for 100 epochs, using a learning rate of 0.0001, and mini-batches of size 16. We trained the model with 80% of the training data, and we used 20% of the training data as the validation set.

The DSSigDataset

For the purpose of our experiments, we have created a dataset consisting of 4000 images with blended signatures with a 300 DPI resolution with both the patch level and stroke level ground truth. Regarding the composition of the dataset, it consists of signature samples on 40 different documents.

Table 1. Experimental results in the test set.

<table>
<thead>
<tr>
<th>Recall</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>89.8%</td>
<td>66.9%</td>
</tr>
</tbody>
</table>

REFERENCES


