

Signature Segmentation from Document Images

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Abstract—In this paper we propose a novel method for the extraction of signatures from document images. Instead of using a human defined set of features a part-based feature extraction method is used. In particular, we use the Speeded Up Robust Features (SURF) to distinguish the machine printed text from signatures. Using SURF features makes the approach generally more useful and reliable for different resolution documents. We have evaluated our system on the publicly available Tobacco-800 dataset in order to compare it to previous work. Finally, all signatures were found in the images and less than half of the found signatures are false positives. Therefore, our system can be applied for practical use.

Keywords-Signature segmentation, extraction, local features, SURF, machine printed text, logos

I. INTRODUCTION

Signatures are considered an important biometric modality for identification of individuals and verification of their identity. The widespread use of signatures in everyday life compels researchers to develop systems for automatic signature identification and verification. Over the last few years various online and offline signature identification and verification systems have been reported. Comprehensive surveys are presented in [1], [2]. In addition to that various signature verification competitions have also been organized, such as [3].

In nearly all cases automatic systems are trained, tested and optimized on data where signatures are present in a pre-segmented form. These signatures are usually collected using special devices and are available to automatic systems so that verification and or identification can be readily applied. However, in real world scenarios signatures usually exist on documents where they sometimes overlay or touch machine printed text. Examples of such documents include bank drafts, forms, invoices, forensic documents such as wills, suicide notes, etc. In order to apply verification or identification, signatures must be segmented from printed text and extracted from these documents. This is a substantial task which if performed correctly will take automatic signature verification systems to a new level where a system can be presented with the full document and after segmentation of signatures verification or identification can be performed.

Different approaches have been presented for extraction of handwritten text from machine printed text. They are usually

based on global thresholding or feature extraction and comparison on the connected component level [4], geometrical structure modeling of printed text and handwriting [5] [6], feature extraction on word level [7]. However, only few approaches are available for signature segmentation.

Djeziri et al. [8] proposed an approach to extract signatures from check backgrounds. This approach is inspired from human visual perception and is based on filiformity criteria whose specialized task is to extract lines. Based on filiformity measure contour lines of objects are differentiated from handwritten lines.

To segment signatures from bank cheques and other documents Madasu et al., [9] proposed an approach based on sliding window to calculate the entropy and finally fit the window to signature block. A major problem of this approach is that it is based on a priori information about the location of the signature.

Zhu et al. [10] proposed an approach based on multi-scale structural saliency map for signature detection in document images. Along with this approach they introduced a publicly available dataset known as the Tobacco-800 that contains about 900 labeled signatures in 1290 document images.

In [11] the method for signature detection by Zhu et al. [10] is combined with signature matching to provide a complete framework for document verification based on signatures.

Mandal et al. [12] proposed an approach using conditional random field for segmentation of signatures from machine printed documents. The result of this approach is reported on a subset (105 images out of 1290 images) of the Tobacco-800 dataset. This approach requires a large number of training samples to actually differentiate between printed text from signatures. In addition, the behavior of this approach in presence of logos and handwritten annotations are not reported.

Currently the ground truth for signatures in publicly available datasets is only available on the patch level, ground truth for these signatures on the stroke level is still missing. Due to the lack of stroke level signature ground truth most of the approaches are also evaluated only on patch level.

Local features are used neither for segmentation of handwritten and machine printed text nor for the segmentation

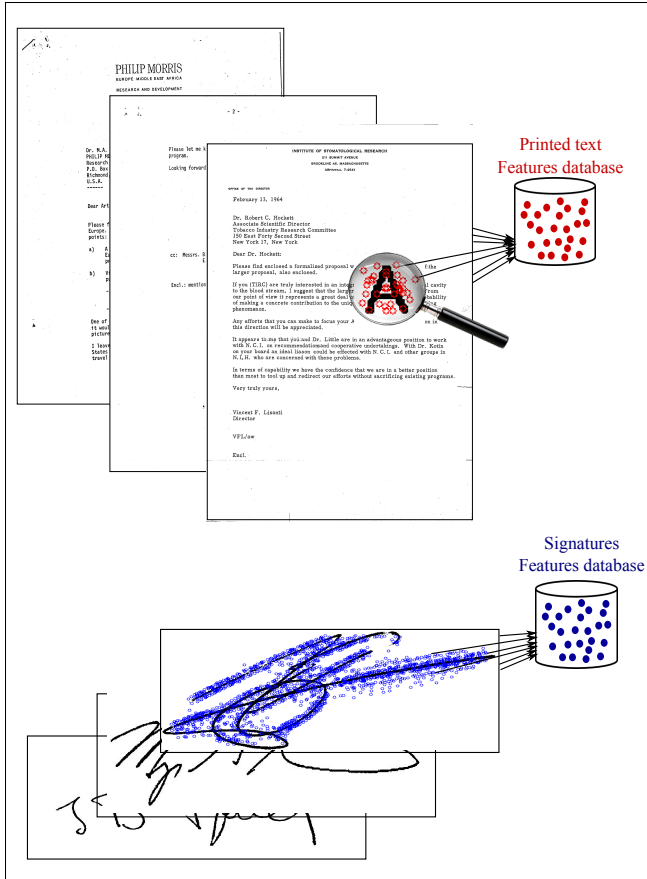


Figure 1: Training

of signature from documents. Local features are extracted from parts of the image thereby disregarding the overall global aspects and are therefore robust to different variations in the image [13], [14]. Local features have already shown very promising results in different domains e.g., character detection in scenes [16], and handwritten character recognition [17]. Due to the results of local features in different domains and their robustness against variations in image, we based our method on local features.

In this paper we propose a novel method for segmentation of signatures from machine printed text using a part based method. In particular, the Speeded Up Robust Features (SURF) are used. SURF is a robust, translation, rotation, and scale invariant representation method. It extracts the key points/points of interest from an image, e.g., the document containing machine printed and handwritten text. The method is evaluated on publicly available the Tobacco-800 dataset.

The remainder of this paper is organized as follows. First, Section II provides an overview of the method proposed in the paper. Second, Section III introduces the dataset used for evaluation of the proposed method. Subsequently, Section IV describes evaluation methods and experimental

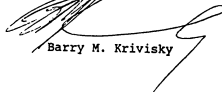
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Figure 2: Original document

results. Finally, Section V concludes the paper and provides an overview of future work.

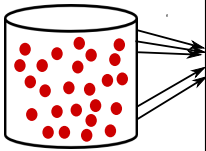
II. METHODOLOGY

For training we used 10 documents from the Tobacco-800 dataset containing machine printed text and signatures. To train the system it is required that all the machine printed text is separated from the signatures. As the Tobacco-800 dataset does not include ground truth for machine printed text, we manually generated two new images for each document, i.e., printed text and signatures image. All of these generated images were used for training. Connected components are extracted for each of the printed text as well as signature image of training set.

SURF is a part based approach that represents image as a set of keypoints. As part based approaches extract keypoints from the parts of image (which represent local features), it brings robustness against different variations in the image [13], [14].

For each of the keypoints a 128 bit descriptor is extracted that represents the keypoint. This descriptor is used to find the similarity between different keypoints. For extraction of SURF features we used a Hessian threshold of 400, i.e.,

Printed text
Features database



Signatures
Features database

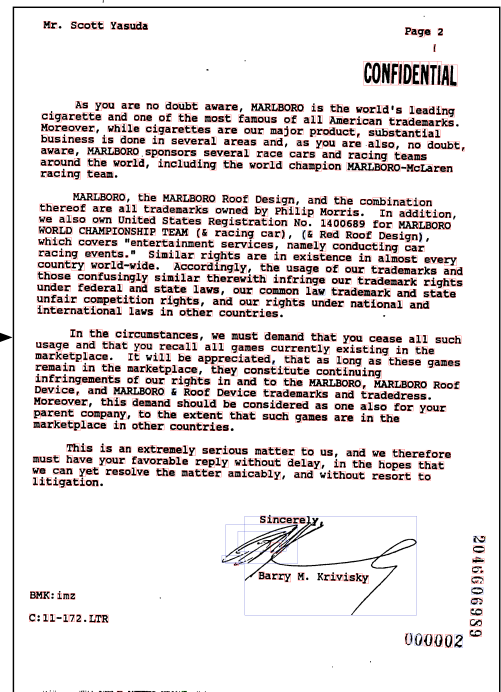
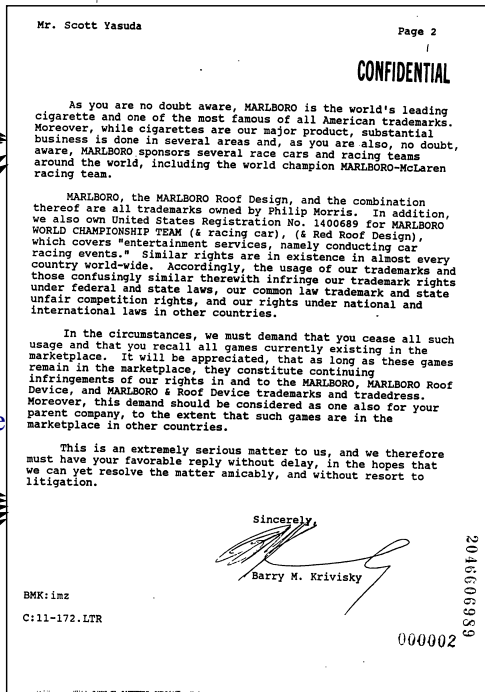
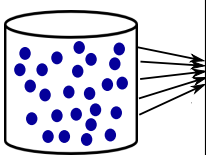


Figure 3: Extracted and marked connected components from question document image

all the keypoints having Hessian threshold less than 400 were neglected. This filtering is done to neglect unimportant features from the images.

For all the connected components from the printed text image, the corresponding extracted keypoints and their respective descriptors are added to printed text features database. Similarly, for each connected component of signature image, extracted keypoints and their respective descriptors are added to signature features database. These two databases serve as a reference for the matching of the features during testing. Figure 1 shows the training procedure of our method.

To segment a signature from a document in the test set (as in Figure 2) which contains both signatures as well as printed text, connected components are extracted. Again for each connected component SURF features are extracted. The descriptor of every keypoint is compared with all the descriptors of printed text keypoints and signature keypoints from the reference databases. The Euclidean distance metric is used as a distance measure. Finally, for the classification of the connected component a majority voting approach is applied. If a connected component's keypoint has less Euclidean distance to the signature keypoints as compared to the printed text keypoints, one vote is added to the signatures class and vice versa. The process is repeated until all of the connected components are assigned to one of the two classes (See Figure 3). Once all of the connected components

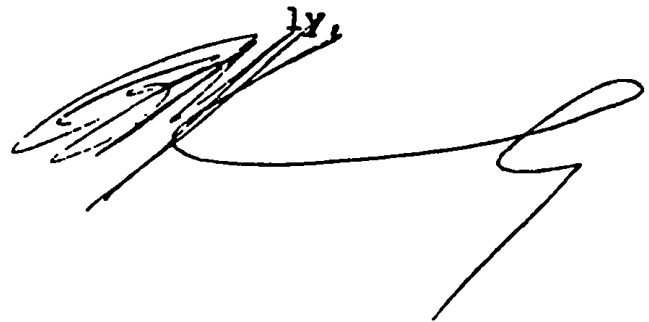


Figure 4: Extracted Signature

are marked as printed text/signature, separate image for signature is generated. To segment the signature from the test document, the original image is cloned and bounding boxes of all connected components of printed text are filled with white color on that image, which in turn results in a segmented signature image.

As a post processing step horizontal run length smearing is performed on the segmented signature image. Applying smearing merges all of the neighboring components. Connected components are extracted from smeared images and all of the small connected components are neglected. Remaining components are considered as signature patches. Figure 4 shows extracted signatures from the document of

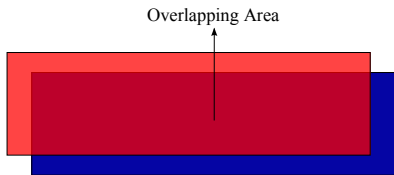


Figure 5: Overlapping area between ground truth (RED) and detected (BLUE) signature patch

Figure 2. One of the main advantages of our approach is that it requires very limited number of training samples.

III. DATASET

Currently, to the best of the authors’ knowledge, there are two publicly available datasets that contain information about signature zones, i.e., the Tobacco-800 dataset [10] and the Maryland Arabic dataset [19]. The Tobacco-800 dataset contains 1290 images with machine printed and handwritten text in English as well as 900 labeled signatures. The Maryland Arabic dataset contains 169 handwritten images with both English and Arabic text along with 149 labeled signatures.

To generate results comparable to the other approaches like [10] evaluation of the proposed method is performed on the Tobacco-800 dataset. The Tobacco-800 dataset contains mixed images with machine printed text, signatures, handwritten annotations and logos. However, the ground truth of this dataset only contains information about logos and signatures on the patch level. As mentioned in Section I the document analysis community has recently started considering the problem of signature segmentation, therefore in the available datasets we currently only have the patch level ground truth information about signatures, but not on the stroke level.

To compare our method with the recently proposed method by Mandal et al., [12], we have also used subset containing only machine printed text and signatures from the Tobacco-800 dataset.

IV. EVALUATION

To evaluate the performance of the proposed method the precision and recall measures are used. As mentioned in Section III, the ground truth contains only patch level information of the signatures. Therefore we also calculated the precision and recall on the patch level. The signature is considered detected if there is at least 40% of overlap between the ground truth and the detected signature patch. Figure 5 illustrates the overlapping criteria used to evaluate signature segmentation.

The evaluation results of the proposed method are presented in Table I. This method has recall of 100%, which means that all the signatures are extracted successfully. A minor drawback of our method is, however, that the precision

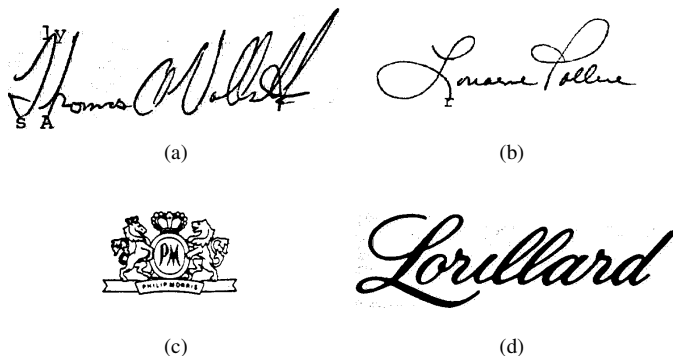


Figure 6: Examples of correctly segmented signatures (a,b) and false positives (c,d)

Table I: Signature Segmentation results on patch level

Method	Precision%	Recall%
<i>Proposed method</i>	56.52	100
<i>Mandal et al.(105 images) [12]</i>	not reported by authors	98.56
<i>Guangyu et al. [11], [10]</i>	not reported by authors	92.8

of our is method is currently quite low. One reason is that we have also considered those images which contain logos and therefore logos are sometimes marked as signature patches. Adding the class “logo” might overcome this problem.

Figure 6 shows some of the segmentation results of our method. Qualitatively the correctly segmented signatures are comparable to manually cropped signatures. Also in Figure 6 there are some examples of false positives.

As can be seen, our method performs quite well on a difficult database. More than every second extracted patch is a signature and all signatures are found. This performance is already quite useful for practice as it is often very important to find all signatures. Using simple background knowledge, such as the probable position of signature the application might reject a hypothesis.

V. CONCLUSION AND FUTURE WORK

In this paper a part-based method for extraction of signatures from machine printed text is proposed. The method extracts all SURF keypoints of a questioned image and compares them with the keypoints of reference templates from printed text and signatures’ features databases. The component having more keypoints matched with signatures database is marked as signature otherwise it is marked as printed text.

In our experiments on the Tobacco-800 dataset we have observed that all of the signatures were successfully extracted. However there are some irrelevant patches detected as signature. This is due to presence of another class, i.e., logos in the image. In future we are planning to extend this method to include other classes and to use more complex

classifier, e.g., SVM, which in turn will increase the precision of the method. In addition, we are planning to remove less distinctive features from both classes using the method proposed in [20].

We are also planning to use the methods proposed in [20] for extraction of text touching characters to finally extract the signature strokes.

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