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Research Article

Automatic Signature Extraction from Document Images using Hyperspectral Unmixing

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Abstract: Signature is one of the most important and widely accepted biometric modality. It is the most common biometric used in documents like financial transactions, legal documents, contracts, etc. Over the years, many signature verification methods have been proposed; however, it is a common notion in most of these methods that signature is available separately for verification purposes. In real world scenarios, signatures are not always available separately particularly in forensics. In documents, signatures usually overlap with other parts of the document, like printed text, lines and graphics, where it becomes practically impossible to detect and localize the signature pixels. In this paper, we present a robust and very effective method for signature segmentation from documents using hyperspectral imaging. A comparative analysis of state of the art *key-point detection based method* and proposed *hyperspectral unmixing method are* provided. The preliminary study shows that spectral unmixing offers great potential for automatic signature extraction from document images.

Keywords: Hyperspectral imaging, document image analysis, hyperspectral unmixing, end-member identification, abundance map, HySime, MVES, MVSA

1. INTRODUCTION

The modern day technologies and security requirements demand user authentication at every step. The user authentication and verification is performed based on different biometrics like fingerprint, iris, voice and handwritten signatures [1]. With the advancements in automated user verification and authentication, many methods for the extraction of information and authentication are presented [2- 4].

The handwritten signature is most accepted and commonly used biometric feature [5]. In forensic science, paper document examination is performed to establish genuineness or non-genuineness, or to expose forgery, or to reveal alterations; additions or deletions in the document. The type of documents that prominently come under question may be a sheet of paper bearing handwriting or mechanically-produced text or signatures such as invoices, a forged cheque or a business contract. There are many methods reported over the years for verification of signatures on paper documents [2–4, 6, 7].

The majority of signature verification and writer identification methods reported assume that signatures are available pre-segmented (taken out of the document – having no overlap with other document contents like text, lines, stamps or graphics), and these pre-extracted signatures are directly provided to the system. Moreover, the publicly available signature databases also provide pre-segmented handwritten signatures from the documents for verification.

On the other hand, in real world, signatures are usually written on documents like bank cheques, invoices, wills, letters and business contracts, where they overlap with other information present in the document i.e. text, lines, stamps or graphics. In such cases it becomes very difficult to extract signature pixels from these overlapping regions using simple image processing techniques. In order to acquire effective results from state of the art

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signature verification methods, it is necessary to segment signatures out of the document [8].

Hyperspectral imagery has found its application in many remote sensing, biomedical and vegetation analysis fields and is now becoming an effective forensic tool for many applications. In this work, a method is presented to segment signatures from paper documents using the hyperspectral document images. Spectral unmixing techniques [9, 10] proposed for remote sensing satellite hyperspectral images are used in this research for the segmentation of signature pixels from the paper documents.

2. SIGNATURE EXTRACTION AND HYPERSPECTRAL UNMIXING METHODS

Signature segmentation using hyperspectral image processing techniques is an emerging field in the area of document analysis. There are many methods reported to extract handwritten text from the printed text based on neural networks, hidden Markov model (HMM), trained Fisher classifier and Markov random fields, etc. [11–15].

The filiformity criteria and hamming measure have also been reported in the literature for signature extraction [16–18]. A public dataset, namely Tobacco-800, consisting of complex document images containing patch level information for 900 signatures and other related information is available [19]. A Speeded up Robust Feature (SURF) [20] key point detection based technique is presented in the literature for segmentation of signatures from documents in Tobacco-800 dataset [8].

All these techniques, work well in cases where signatures are available pre segmented without any overlap, but if the signature overlaps any other part of the document like lines, text, stamps and graphics, the performance of these techniques drop significantly.

A database of 100 hyperspectral signature documents is reported in [21, 22]. The dataset contains patches of signature documents with different scenarios like partial, none and complete overlap of signatures with text and graphics as illustrated in Fig. 1. SURF [20] key point detection based method is used in this reported paper to segment the signatures from documents. This method uses the spectral property of the

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

Fig. 1. Signature samples :(a) Sample data-cube; (b) None; (c) Partial; (d) Complete overlap.

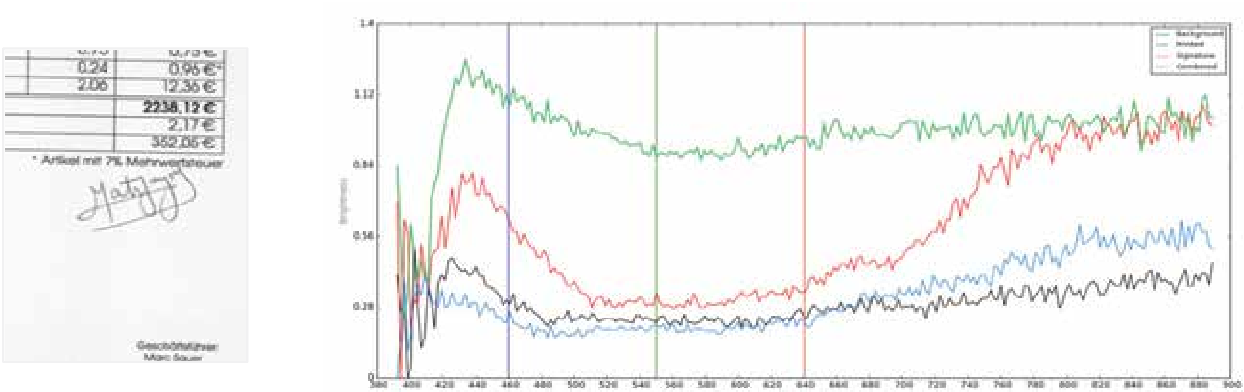


Fig. 2. Signature image band and its spectral signatures.

hyperspectral documents i.e. the signature is present in lower wavelengths and vanishes from the high wavelength bands of the document as shown in Fig 2. The spectral curve in blue is showing the combined spectral behavior of the overlapping region of the document. The reported key point detection based method shows promising results when the signature is not overlapping with other parts of the document i.e. printed text, lines and stamps, but the performance of the key point detection based method decreases in cases where signature is overlapping with other parts. In the field of hyperspectral remote sensing, various hyperspectral unmixing techniques are reported to identify and extract end-members (pure materials) and their respective abundance fractions present in the dataset [23]. The geometrical based spectral unmixing approaches for the linear mixing model like minimum volume enclosing simplex (MVES) [9] and minimum volume simplex analysis (MVSA) [10] are state of the art methods for the solution of hyperspectral unmixing problem. MVES uses a cyclic minimization using linear programs for the solution of minimum volume (MV) problem [24], while MVSA is a robust and enhanced version of MV concept.

In hyperspectral images, if A denotes the end-member signature matrix, s[n] denote the abundance map of nth abundance vector and w[n] denotes noise then linear mixture model can be given by Eq. 1, where x[n] shows the hyperspectral data-cube.

$$x[n] = As[n] + w[n] \tag{1}$$

The hyperspectral signature documents can be considered as a linear mixture of the different materials present in the document i.e. paper, printed text, signature and other graphics.

Therefore, the problem of our signature mixture (overlap) with other parts of the document is treated as a hyperspectral unmixing problem and state of the art spectral unmixing algorithms can be used to segment signature pixels from the documents which are difficult to extract otherwise. The unmixing techniques identify the end-members present in the document, along with their abundances. The MVES and MVSA techniques do not require pure pixels to be present in the dataset. The method successfully extracts signatures from all kind of documents (none, partial and complete overlap). The methodology is discussed in detail in the next section.

3. METHODOLOGY

3.1 Dataset and Preprocessing

The dataset reported by Malik et al. [21] is used in this work. The dataset contains patches from 100 document images, scanned using hyperspectral camera with a spectral resolution of 2.1 nm. The documents used contain printed text mostly in black but include colored graphics and logos.

Signatures are performed using different type of pens including oil and gel pens, having blue and black inks. The dataset contain document examples of partial, none and complete overlapping signatures. The ground truth reported previously for this dataset was available at signature bounding box level [21].

The bounding box level ground truth serves well in cases where signature is not overlapping with other parts of the document, but in partial or complete overlap of the signatures this ground truth does not give us the true evaluation of the performance of our system. The pixel level ground truth for the complete dataset was generated in this research, which will also be beneficial for any future work on this dataset. The pixel level ground truth is generated by manually marking the overlapping pixels of the signature; the results at different steps of the ground truth generation process are given in Fig. 4.

The drawback of hyperspectral data is that along with huge amount of information it contains noise. In this dataset, it was observed that low wavelength bands near 400 nm contain huge amount of noise (Fig. 3) and it is essential to remove these bands to produce correct results. An automatic noise level detection and estimation technique is used in this work. It uses patch-based noise level estimation algorithm for images to estimate noise level in each band of the document [25].

A threshold based on median value of noise levels is selected to successfully remove the noisy bands from the signature documents. The remaining

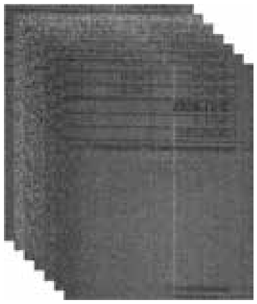


Fig. 3. Noisy bands.

Fig. 4. Pixel level ground truth generation steps.

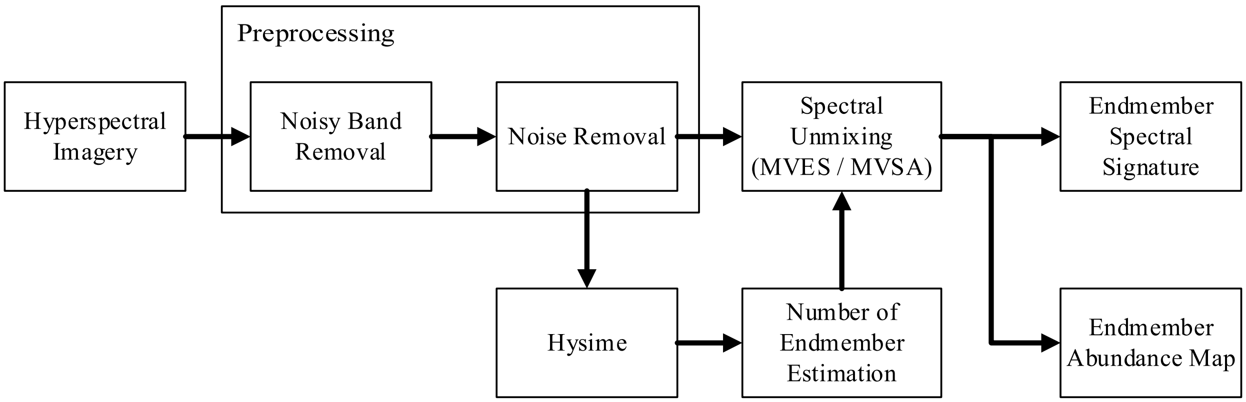


Fig. 5. Flow diagram of Hyperspectral Unmixing method for signature segmentation.

dataset is used to effectively segment signatures from the documents. There is also small noise present in remaining bands hence averaging and median filters are applied to minimize the effect of this noise.

3.2 Hyperspectral Unmixing Methods

The SURF key-point based method reported by Malik et al. [21] was very successful in segmenting signature from documents in which there was no overlap between signature and other parts of the document i.e. text, line and stamps. But with almost all the signatures that were in partial or complete overlap with other parts; the key-point based method reported was not successful to segment the overlap portion of the document (Fig. 6). In real scenarios signatures usually overlap with other parts of the document; so there is a need for signature segmentation techniques that could extract these overlapping pixels in a more effective manner. In this research, spectral unmixing methods are used to segment signatures from documents; i.e., MVES and MVSA. Along with these methods, two variants are also implemented to improve the signature extraction results. The MVES and MVSA algorithms require an estimate of the number of end-members present in the document to calculate the spectral response of end-members along with their fractional abundances. Hyperspectral signal subspace identification by minimum error (Hysime) [26] is used for the subspace identification and number of end-member estimation. This estimated number of end-members is used by the MVES and MVSA algorithms. The unmixing algorithms provide the spectral signatures and abundance maps of the end-members present in the dataset. The flow diagram of the unmixing methods for hyperspectral document images is given in Fig. 5.

Once the abundance maps of the end-members are generated, we discard those abundance maps which spread throughout the document and select the abundance maps relating to the signatures. The selected abundance map corresponding to the signature is used to generate the segmented signature pixels by applying Sauvola binarization algorithm [27]. The results obtained from MVES

(a) (b) (c)

Fig. 6. (a) RGB Image; **(b)** Key-point Detection Method result; **(c)** Method 2 result.

and MVSA algorithms are given in Table 1. These results outperform previously proposed key-point detection method [21] especially in cases where signatures are overlapping with other parts of the document. Due to highly mixed nature of the signature and text/lines/stamp pixels in the overlapping regions of the document as depicted in the spectral signatures of the document (Fig. 3), few signature pixels are still missing in the final output. To improve the signature pixel count in the overlapping parts of the signature, it is proposed to combine the signature output of both methods (MVES and MVSA) to get better results. For future reference in this paper the union of MVES and MVSA results is called Method 1 and its results are given in Table 1. Also to further improve the performance of our system and signature pixels that are still missing in overlapping regions; signatures obtained from Method 1 are skeletonized as shown in Fig. 5 and based on small minimum distance (< 5 pixels) between the edges of skeletonized structure pixel filling is performed. For further reference in this paper this method is called Method 2. The noise removal is performed at each step to remove small noisy objects that does not belong to the signatures. The final results of Method 2 are also given in Table 1.

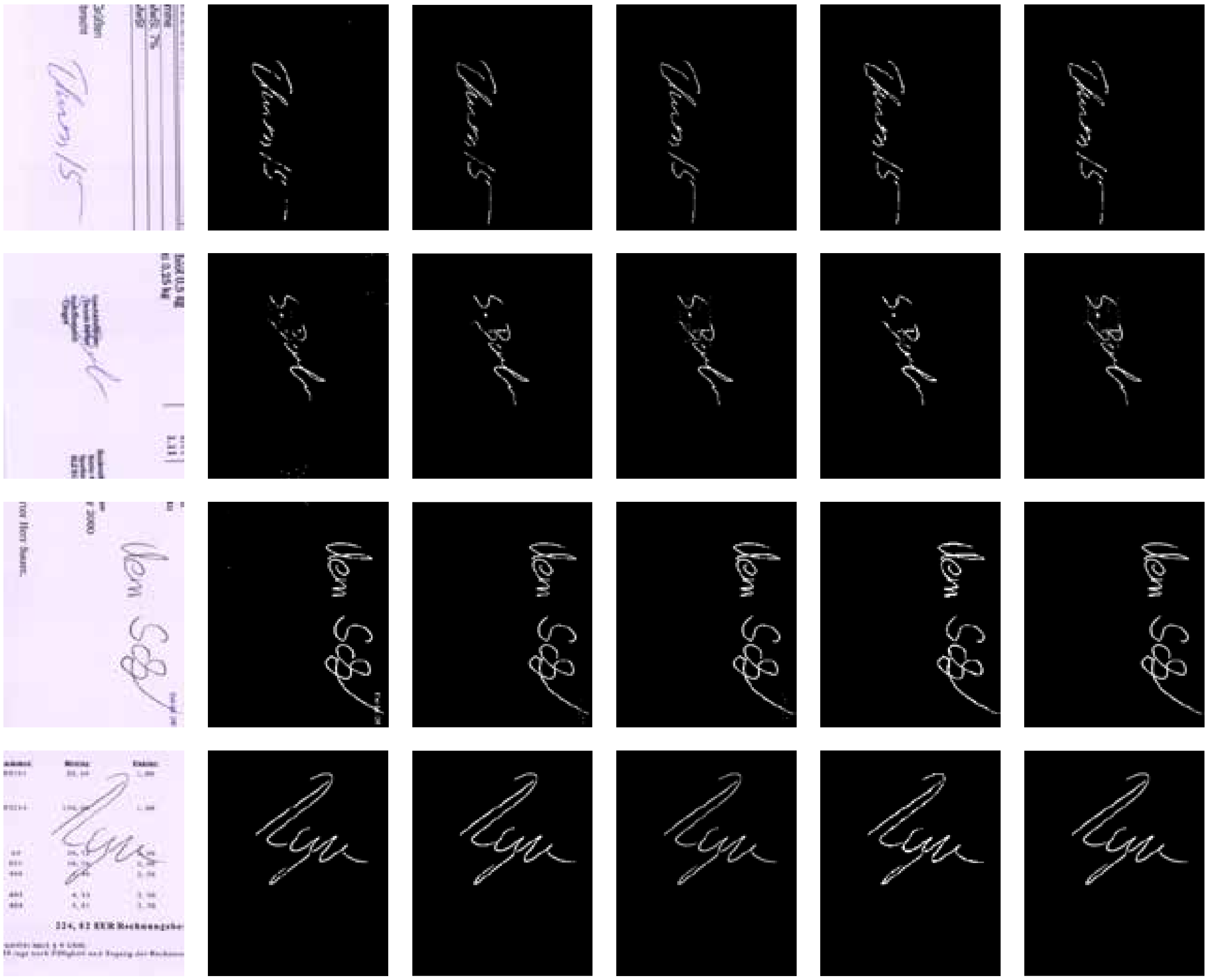
4. RESULTS AND EVALUATION

The results obtained from different methods are given in this section. The results shown in Table 1 clearly depict that the signatures with overlapping parts are segmented more accurately by using

Fig. 7. Skeleton structure for signature.

Table 1. RGB images and final results of different methods.

RGB Image	Key-point Method	MVES	MVSA	Method 1	Method 2



spectral unmixing methods.

The bounding box method used by Malik et al. [21] to report the performance of system gave good results for the documents where the signatures had very little or no overlap with other parts of the document and where there was little noise present in the segmented signature bounding box. But when the overlap of signature happens, this evaluation method does not give clear understanding of the missing overlapping pixels. So a pixel level evaluation method is adopted in this study, to get clear understanding of the segmented signature pixels that are overlapping.

The performance of our system is reported by using precision, recall and F measure values. Precision representing how relevant our retrieved signatures are, i.e. what percentage out of the retrieved signature pixels are corresponding to signatures, and Recall is indicating that out of all signatures pixels which are present in the document how many of them are part of retrieved signature pixels. The F measure is the harmonic mean of precision and recall and it gives an overall performance measure of the system. The precision, recall and F measure for the database of 100 documents is calculated for different methods and is given in Table 2.

Key point detection based method performs with very high precision but the recall is low meaning that there are many signature pixels that

Table 2. Precision and recall complete dataset.

	Precision (%)	Recall (%)	F Measure (%)
Key Point Detection Method	92	80	85.6
MVES	85	86	85.5
MVSA	90	82	85.8
Method 1	81	95	87.5
Method 2	81	95	87.5

Table 3. Precision and recall overlapping signature documents.

	Precision (%)	Recall (%)	F Measure (%)
Key Point Detection Method	76	76	76
MVES	80	81	82
MVSA	83	84	84
Method 1	76	91	83
Method 2	75	92	83

are missed in the final segmented signature. The unmixing algorithms give us good precision but the recall is very high meaning that we are extracting most of original signature pixels. The F measure clearly gives unmixing methods edge over the previously reported methods.

The better performance of unmixing methods gets clearer when we evaluate our system on the basis of documents in which signatures are overlapping with other parts of the document. The results obtained for only the overlapping signature are shown in Table 3. It depicts that result for the key-point detection method has dropped down in comparison to the hyperspectral unmixing methods. The unmixing algorithms have significantly improved the precision and recall of our system in cases where signatures are overlapping. The system is successfully extracting most of the signature pixels as compared to the key point based methods. The F measure is also showing clear superiority of unmixing methods over other methods.

5. CONCLUSIONS

In real world scenario, signatures on documents overlap with other parts of the document like text, lines, stamps and graphics, and it becomes very difficult to segment signature pixels from these documents if signatures are not available pre-segmented. In this work hyperspectral unmixing methods using minimum volume simplex are used for signature segmentation from document images. The proposed unmixing methods successfully extract signature pixels; which is difficult using other image processing techniques like key point detection. The images captured in visible range of electromagnetic spectra are also not sufficient for overlapping signature extraction. The signature extraction techniques using hyperspectral unmixing will open new dimensions in the field of signature extraction and verification. The proposed signature extraction methods can play a vital role in determination of authenticity of documents. In future work the signature segmentation process can be automated to work as a pre-processor for signature verification systems. It can enhance the handwritten signature analysis capabilities performed by different forensic systems.

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