Automatic Signature Segmentation Using Hyper-spectral Imaging

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***Abstract*— In this paper, we propose a method for automatic signature segmentation using hyper-spectral imaging. The proposed method first uses the connected component analysis and local features to segment the printed text and signatures. Secondly, it uses spectral response of text, signature, and background to extract signature pixels. The proposed method is robust, and remains unaffected by color and intensity of the ink, and by any structural information of the text, as the classification relies exclusively on the spectral response of the document. The proposed method can extract signature pixels either overlapping or non-overlapping from different backgrounds like, logos, tables, stamps, and printed text. We used high-resolution hyper-spectral imaging to study and classify 300 documents with varying backgrounds. We evaluated the proposed classification method and compared results with the state-of-the art system. The proposed method outperformed the state-of-the-art system and achieved 100% precision and 84% recall.**

***Keywords*-Local Feature Analysis, SURF, Signature Segmentation, Hyper-spectral Imaging**

I. INTRODUCTION

Handwritten signatures are important biometric traits due to their social and legal acceptance for individual identification and verification and to identify fraud in finance and banking industry [1], [2]. The widespread use of signatures in daily life justifies development of systems for automatic signature segmentation and verification [3]. Handwritten signature segmentation and verification is a difficult task due to the free-flow nature of handwriting, and because signatures some times are written on top of logos, lines etc. Humans use three independent channels for color perception [4], and that is the reason for use of trichromatic RGB color space in printers, cameras, and scanners. Similarly, RGB color space consists of three colors red, green, and blue [1]. Figure 1 shows the spectrum of color which contains the ultraviolet, visible, and infrared region. Humans can see things that lie only in the visible region. According to RGB color space blue channel starts from 400 nm to 500 nm that is perceived by first type of cone. 450 nm to 630 nm range is perceived by second type of cone and called as green channel. Blue channel starts from 500 nm to 700 nm that is perceived by third type of cone. So in this way humans perceive and visualize colors in RGB color space [1], [5].
Various research groups are working on both offline and online signature verification and identification systems [6], [7], [8]. However these approaches are not fully realistic, as they assume that signatures are already segmented or they do not overlap with other information like text, logos, and noise etc., as shown in figure 2. In order to perform signature verification, it is required to first segment signatures from the document. If segmentation process performed efficiently, it will improves the overall performance and accuracy of the verification process. As humans are trichromatic by nature and machines are not trichromatic. Hyper-spectral imaging (HSI) enables collecting and processing information across the electromagnetic spectrum. HSI provide more fine and detailed representation than RGB color space [9]. HSI has application in different fields like astronomy, agriculture, bio-medical imaging, geo-science, and mineralogy [10], [6], [11].
Existing methods for signature segmentation use binary, gray scale, or RGB images for segmentation [12], [13]. They use color or structural information of text to segment the

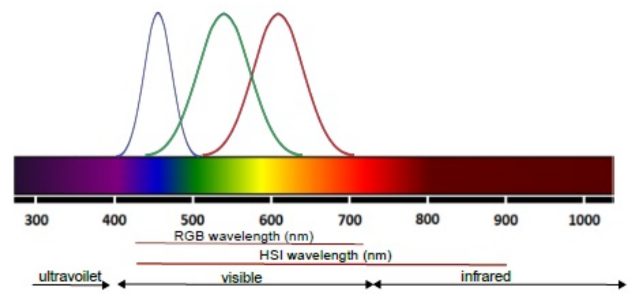

Fig. 1: Color Spectrum

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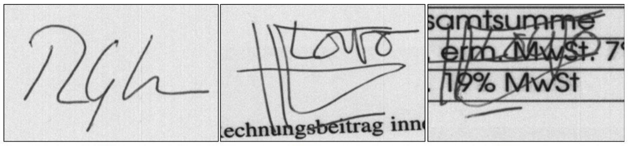

(a) (b) (c)

Fig. 2: Signature Scenarios in documents. (a) No Overlap (b) Partial Overlap (c) Complete Overlap

signature. However these methods are not effective as they assumes that signatures are already segmented, signatures are not overlapping with other text, or they know the exact position of signature which is unrealistic.

We propose a system for automatic signature segmentation using hyper-spectral information and local features of the text. The proposed system is the optimized version of the state-of-the-art system presented by M. Malik et al. [14] with 100% precision and 73% recall. The recall of the state-of-the-art system is low as the band selection for printed and handwritten text is prone to error. In this paper, we improve upon the state-of-the-art by separating machine printed text and signature using the part-based features and connected component analysis [15], and then use hyper-spectral information for extracting signature pixels. We evaluated our method on the same hyper-spectral signature dataset used by the state-of-the-art system and achieved significantly better results then the state-of-the-art.

The rest of this paper is organized as follows. Section II provides an overview of the existing methods and the usage of HSI in different areas of research like document analysis, Medical, and agriculture etc. Section III gives details of the data set we used in our experiments. Section IV provides details of our automatic signature segmentation method. In the section V results are presented. The paper is concluded with discussion and future work.

II. RELATED WORK

Hyper-spectral imaging, also called optical reflectance imaging, is a non-destructive method that calculates reflectance properties of a document with finer details and high resolution [16], [17], [18]. In this section, we provide an overview of techniques developed in the past few years along with the current research trends.

Signatures are very important biometric trait due to their widespread use in person identification and verification in daily life [12], [19]. Financial institutions use signatures for verifying persons identity in administrative and transaction processes [20], [21].

Over the last few years several efforts have been done in the area of spectral imaging [22]. Easton et al. [13] present a novel and efficient method for forensic document comparison. A very efficient HSI system was developed by Archives of Netherland for the analysis of historic documents in libraries [23]. HSI is mostly used for text recovery, segmentation and enhancement of historic documents. Shiel et al. [11] performed segmentation and text recovery using HSI. They per formed segmentation using a 16th century old book for segmentation whose cover was pasted down and the late medieval texts which was written using multi-ink combination. Aalderink et al. [24] propose a technique for restoring historic documents. They used spectral properties of ink and extract the damaged areas of a 19th century book by mapping ink particulars. Lettner et al. use multi-spectral characteristics with AI techniques to enhance the visibility of historic documents [25] and perform segmentation on those documents to save the text.

HSI is becoming increasingly popular due to algorithmic advances like unmixing of spectra captured in a single image pixel [26], creating high resolution HSI Images with the aid of high spatial density RGB images of the same scene [27] and methods for compressive sensing of HSI data [28].

One of the key areas in document image analysis using HSI is ink mismatch detection for detecting forgeries and fraud [29]. G. Reed et al. use HSI to differentiate between different inks and found it very useful for segmentation purpose. They provide a detailed discussion about how different inks red, green, blue, and black have different spectral response values which are useful for segmentation [30]. Z. Khan et al. [31] use handwritten documents made using different ink combination. They analyze the spectral response of inks in 33 bands and found it useful for detecting forgery with the assumption that forged part and genuine part contain same amount of text. They released a HSI dataset [32] publicly for ink mismatch detection and use k-mean clustering for detecting forgery.

M. Malik et al. [14] use hyper-spectral information for segmenting the signature pixels. This is the first system reported on hyper-spectral signature data set. They handle both the overlapping and non-overlapping case of signature on text where signature may complete overlap, partial overlap, or no overlap with the background, lines, logos etc. They extract signature pixels with precision and recall of 100% and 73%.

III. DATASET

In the last few years, many methods are presented for signature segmentation from binary, gray scale, and RGB images [7], [33]. Up to the best of author's knowledge, there are only two publicly available datasets, i.e., Tobacco_800 [33] and Maryland Arabic [34] which can be used to evaluate the task of signature segmentation from binary document images. The most recent and challenging dataset is presented by M. Malik et al. [14], which consists of 300 invoices with handwritten signatures, captured using a professional high-end hyper-spectral camera. Figure 3 shows the hyper-spectral document capturing setup. The hyper-spectral camera used in the capturing setup covers spectral region starting from ultraviolet (400 nm), visible, and ranges to infrared region (900 nm) with a very fine resolution of 2.1

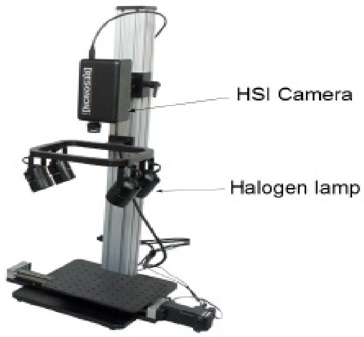

Fig. 3: Hyperspectral Imaging System

Table I: Hyper-spectral Imaging System Specification

Parameter	Values
Specctral Range (nm)	400-900
Spectral Resolution (nm)	2.1
Spectral Channels	240
Spatial Channels	640
Bit Depth	12

nm. Table I shows the complete specification of the hyper-spectral camera used to scan document images. The hyper-spectral signature segmentation data set contains documents with signatures performed by different authors on invoices. The document images in dataset contain both overlapping and non-overlapping signatures with rest of the content of the document i.e., lines, logos, and printed text. Signatures are done using different type of blue and black ink and gel pens.

To evaluate the performance of signature segmentation methods, the data set is further divided into training and test set. The train set contains 30 real representative document images with both overlapping and non-overlapping signatures, while the test set contains remaining 270 images with overlapping, non-overlapping, and no signatures. Patch level ground truth is provided for each image, where a bounding box of signature regions is provided as a ground truth images.

IV. METHODOLOGY

The proposed method for signature segmentation consists of 3 phases. First, the document images are preprocessed to remove noise. Second, connected component labeling and part-based features are used to automatically segment signatures from text. Finally, post processing is to performed to precisely extract signature's bounding box.

On analysis of the hyper–spectral response of document images, it was seen that response of pen ink varies across all of the 240 bands. Figure 4 shows the spectral response

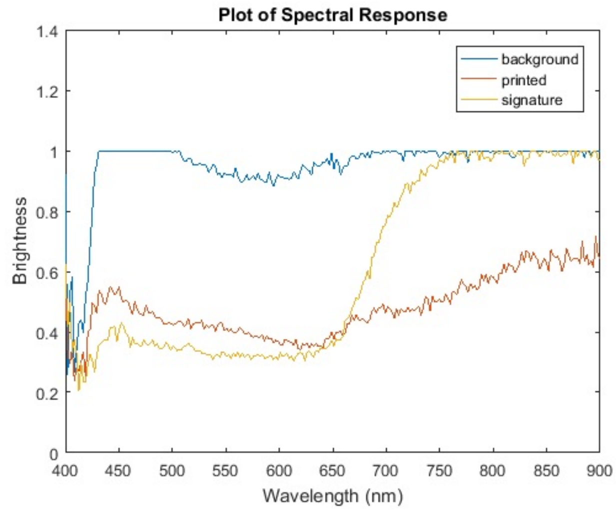

Fig. 4: Spectral Response Analysis

of signature, background, and printed text pixel across 240 spectral bands. The response of printer ink and background is almost consistent across all the bands. However, the response of signature pixels varies a lot, especially in the bands near infrared region. This observation serves as a building block for our methodology.

For training we used 30 document images from the dataset presented by Malik et al. [14] containing signatures and machine printed text. To train the system, printed text is separated from signatures using available ground truth information, which results into two images against each document in training set i.e., printed text image and signature image. The following procedure is performed for signature extraction:

1) Connected components are extracted for each of the printed and signature image present in the training set.
2) Compute the key points and their descriptors using SURF key point detector of all the connected components of the printed text and added to machine printed text (MPT) database. Similarly, key points and their descriptors are computed on all the connected components of signatures and added them to hand written signature (HRS) database as shown in figure 5.

Following steps are performed to segment signature from query image (from test set), which may contain printed text, signature, and overlapped region.

1) Connected components are extracted and for each connected component SURF features are extracted along with their descriptors. The descriptor of every point is compared with all the descriptors of printed text and signatures in the reference databases.
2) K–Nearest Neighbour (K–NN) classifier is used to classify connected components in on of two classes. If a connected component key point has less distance

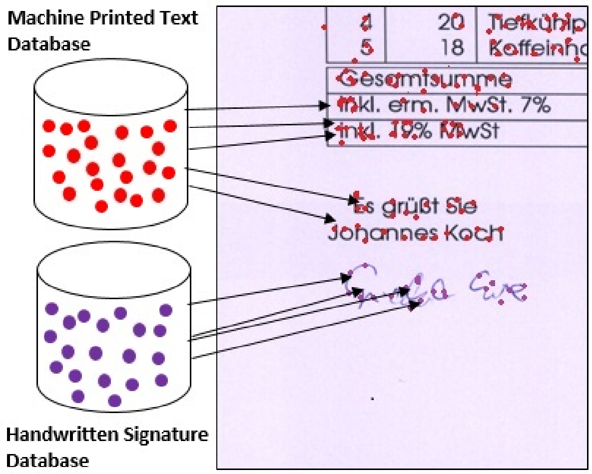

Fig. 5: Machine printed Text and Handwritten Signature Databases using Connected Component

to MPT database descriptors as compared to HRS database descriptors, one vote is added to MP database and vice versa. Repeat this process until all of the connected components are assigned to one of two classes. As overlapping connected component contains both printed text and signature, it can not be classified in one of the two classes based on K–NN distance.

3) To segment signature from overlapping region we use hyper–spectral information. Based on the above observation, the first step is to locate the two most significant and distinguishing bands automatically out of 240 bands which can be used for getting signature pixels. We have to locate the bands that have following characteristics:
   - First band where all of the objects on the hyper–spectral document have non–significant response including signatures named as $\lambda_{\max}$.
   - Second band where everything is visible except signatures named as $\lambda_{\min}$.

To find these two bands $\lambda_{\max}$ and $\lambda_{\min}$ we used local key point detector. Local key point detectors locate most important information in the documents which referred as key points. For the proposed methodology we used SURF as key point detector and also as a descriptor. SURF key point detector is a part based key point detector. As it extracts local information of the parts of the image which makes it more robust against the variations in the image. The proposed method can also work with other key point detection methods such as; SIFT [33], FAST [35], or BRISK [36] etc. Hyper–spectral document images consists of 240 gray scale images each containing the spectral response of the document for that band and we apply local key point detector on each document. In the preprocessing phase noise sparks are removed from the image using averaging and denoising filter. Preprocessed image is then used to find connected components for separating the machine printed and signature text. Once the blobs are located SURF key point detector and descriptor is applied to get local information of the text. The number of key points detected on each image is referred as δ_n, where n represents the band number as shown in figure 6. Band where the amount of key points are maximum is referred to as $\lambda_{\max}$ and the band where the amount of key points are minimum referred to as $\lambda_{\min}$. Once these bands are located, the next step is to separate the signature pixels from the remaining text or information. To do this morphological opening is performed first on the $\lambda_{\max}$ that results in noise and signature pixels. The resulting image is then subtracted from $\lambda_{\min}$ called λ_{sub} so that only the signature pixels remain. To get the signature pixels and remove the noise, morphological closing is performed on λ_{sub} and the resulting pixels are used to extract the actual pixels from the document. In the post processing phase the remaining noise and non text regions are removed using based on geometric property so that only signature pixels remain and noise like border lines, irrelevant dots, and Gaussian noise can be removed.

V. EVALUATION

For evaluation purpose we used precision and recall measures. Precision tells us about the quality of the extracted bounding box. In other words how many bounding box that are extracted are actually signatures as shown in the equation 1. Second measure is recall which tells us how many signature bounding box our algorithm extracted out of all signatures present in the document as shown in equation 2.

$$\text{Precision} = \frac{\text{Retrieved BBOX} \cap \text{Signature BBOX}}{\text{Retrieved BBOX}} \tag{1}$$

$$\text{Recall} = \frac{\text{Retrieved BBOX} \cap \text{Signature BBOX}}{\text{Signature BBOX}} \tag{2}$$

Precision in the field of document analysis is the fraction of extracted signature bounding boxes that are relevant and recall is the fraction of signature bounding box that are retrieved accurately.

As discussed in the previous section we have only patch level ground truth images which we used to find the precision and recall. For every document ground truth image we have a signature bounding box. We calculate precision and recall by assuming that if there is a 50% overlap between the extracted signature bounding box and ground truth bounding box are considered as correct. Results are shown in table II.

We extracted printed text and simple signature using Connected Components and segment out the overlapped signature pixels using hyper-spectral information which improves the system accuracy as compared to the state of the art system. Firstly in the preprocessing phase we remove noise which enhance the signature document image for finding

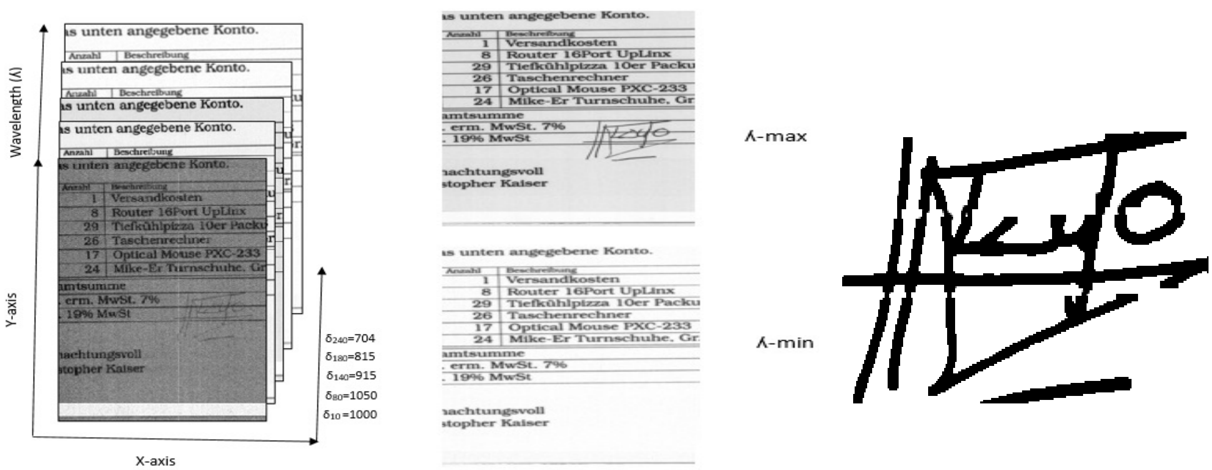

Fig. 6: Signature Segmentation process

Table II: Segmentation Results

System	Precision	Recall
Proposed Mehtod	100%	84%
M. Malik et al. [14]	100%	73%

connected blobs of printed text and signatures and then applied SURF features more intelligently by working only on the overlapped region which helps to improve the overall performance. We use the same experimental setup with 30 images as training set and 270 for testing and standard performance measures. We improved the recall from 73% to 84% with 100% precision. Secondly in the post processing phase signature bounding boxes are formed more accurately by removing the background noise and pixels noise which improves the bounding box quality.

VI. Future Work And Conclusion

In this paper we present a method for automatically segmenting signature pixels from hyper-spectral document images. We improve the state of the art system which is the pioneer work in the signature segmentation field using HSI. Our method is the optimized version of the state-of-the-art system. We use Connected Component analysis and SURF features with preprocessing and post processing steps, makes the extracted signature bounding boxes more accurate and efficient. Our method does not use any structural information of the text rather it uses the local features of the text and the spectral reflectance produced by the object. As discussed in section IV, pen ink, gel ink, printed text and background have different spectral responses at different bands. Our main task was to identify those distinguishing bands and use them for segmentation. The proposed method is also more realistic that it caters real time scenarios of overlapping and non–overlapping text.

In the future we plan to improve ground truth from patch level to stroke level and increase the scope of our system by incorporating more realistic documents for segmenting and also used for verification purpose.

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References

[1] R. Hunt, *The Reproduction of Colour*. The Wiley-IS&T Series in Imaging Science and Technology, Wiley, 2005.

[2] W. Song, S. Uchida, and M. Liwicki, "Comparative study of part-based handwritten character recognition methods," in *ICDAR*, pp. 814–818, IEEE, 2011.

[3] S. J. Pinson and W. A. Barrett, "Connected component level discrimination of handwritten and machine-printed text using eigenfaces," in *ICDAR*, pp. 1394–1398, IEEE, 2011.

[4] S. Schneider, R. J. Murphy, and A. Melkumyan, "Evaluating the performance of a new classifier–the gp-oad: A comparison with existing methods for classifying rock type and mineralogy from hyperspectral imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 98, pp. 145–156, 2014.

[5] I. Ruyter, K. Nilner, and B. Möller, "Color stability of dental composite resin materials for crown and bridge veneers," *Dental Materials*, vol. 3, no. 5, pp. 246–251, 1987.

[6] M. A. Calin, S. V. Parasca, D. Savastru, and D. Manea, "Hyperspectral imaging in the medical field: present and future," *Applied Spectroscopy Reviews*, vol. 49, no. 6, pp. 435–447, 2014.

[7] R. Mandal, P. P. Roy, and U. Pal, "Signature segmentation from machine printed documents using conditional random field," in *ICDAR*, pp. 1170–1174, IEEE, 2011.

[8] J. Sita, B. Found, and D. K. Rogers, "Forensic handwriting examiners' expertise for signature comparison," *Journal of Forensic Science*, vol. 47, no. 5, pp. 1–8, 2002.

[9] C.-I. Chang, *Hyperspectral imaging: techniques for spectral detection and classification*, vol. 1. Springer Science& Business Media, 2003.

[10] D. Lorente, N. Aleixos, J. Gómez-Sanchis, S. Cubero, O. L. García-Navarrete, and J. Blasco, "Recent advances and applications of hyperspectral imaging for fruit and vegetable quality assessment," *Food and Bioprocess Technology*, vol. 5, no. 4, pp. 1121–1142, 2012.

[11] P. Shiel, M. Rehbein, and J. Keating, "The ghost in the manuscript: Hyperspectral text recovery and segmentation," *Codicology and Palaeography in the Digital Age, M. Rehbein and PS und Torsten Schaßan, Eds. Norderstedt: Books on Demand*, pp. 159–174, 2009.

[12] R. Plamondon and S. N. Srihari, "On-line and off-line handwriting recognition: A comprehensive survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 1, pp. 63–84, 2000.

[13] R. L. Easton, K. T. Knox, and W. A. Christens-Barry, "Multispectral imaging of the archimedes palimpsest," in *32nd Proceedings of Applied Imagery Pattern Recognition Workshop*, pp. 111–116, IEEE, 2003.

[14] M. I. Malik, S. Ahmed, F. Shafait, A. S. Mian, C. Nansen, A. Dengel, and M. Liwicki, "Hyper-spectral analysis for automatic signature extraction," in *17th IGS*, 2015.

[15] H. I. Koo and D. H. Kim, "Scene text detection via connected component clustering and nontext filtering," *IEEE Transactions on Image Processing*, vol. 22, no. 6, pp. 2296–2305, 2013.

[16] S. J. Kim, F. Deng, and M. S. Brown, "Visual enhancement of old documents with hyperspectral imaging," *Pattern Recognition*, vol. 44, no. 7, pp. 1461–1469, 2011.

[17] M. Golbabaee and P. Vandergheynst, "Hyperspectral image compressed sensing via low-rank and joint-sparse matrix recovery," in *ICASSP*, pp. 2741–2744, IEEE, 2012.

[18] A. Chakrabarti and T. Zickler, "Statistics of real-world hyperspectral images," in *CVPR*, pp. 193–200, IEEE, 2011.

[19] M. Fairhurst, "Signature verification revisited: promoting practical exploitation of biometric technology," *Electronics & communication engineering journal*, vol. 9, no. 6, pp. 273–280, 1997.

[20] M. C. Fairhurst and E. Kaplani, "Perceptual analysis of handwritten signatures for biometric authentication," *IEE Proceedings - Vision, Image and Signal Processing*, vol. 150, no. 6, pp. 389–394, 2003.

[21] F. Leclerc and R. Plamondon, "Automatic signature verification: the state of the art 1989-1993," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 8, no. 3, pp. 643–660, 1994.

[22] C. S. Silva, M. F. Pimentel, R. S. Honorato, C. Pasquini, J. M. Prats-Montalban, and A. Ferrer, "Near infrared hyperspectral imaging for forensic analysis of document forgery," *Analyst*, vol. 139, pp. 5176–5184, 2014.

[23] R. Padoan, T. A. Steemers, M. Klein, B. Aalderink, and G. De Bruin, "Quantitative hyperspectral imaging of historical documents: technique and applications," *ART Proceedings*, 2008.

[24] B. Aalderink, M. Klein, R. Padoan, G. De Bruin, and T. Steemers, "Clearing the image: A quantitative analysis of historical documents using hyperspectral measurements," *37th AIC*, 2009.

[25] M. Lettner and R. Sablatnig, "Spatial and spectral based segmentation of text in multispectral images of ancient documents," in *10th ICDAR*, pp. 813–817, IEEE, 2009.

[26] N. Akhtar, F. Shafait, and A. Mian, "Futuristic greedy approach to sparse unmixing of hyperspectral data," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 4, pp. 2157–2174, 2015.

[27] N. Akhtar, F. Shafait, and A. Mian, "Bayesian sparse representation for hyperspectral image super resolution," in *CVPR*, pp. 3631–3640, 2015.

[28] Z. Khan, F. Shafait, and A. Mian, "Joint group sparse pca for compressed hyperspectral imaging," *IEEE Transactions on Image Processing*, vol. 24, no. 12, pp. 4934–4942, 2015.

[29] L. J. Denes, P. Metes, and Y. Liu, *Hyperspectral face database*. The Robotics Institute, Carnegie Mellon University, 2002.

[30] G. Reed, K. Savage, D. Edwards, and N. N. Daeid, "Hyperspectral imaging of gel pen inks: An emerging tool in document analysis," *Science and Justice*, vol. 54, no. 1, pp. 71–80, 2014.

[31] Z. Khan, F. Shafait, and A. S. Mian, "Towards automated hyperspectral document image analysis," in *2nd Int. Workshop on AFHA, Washington DC, USA*, pp. 41–45, 2013.

[32] Z. Khan, F. Shafait, and A. Mian, "Hyperspectral imaging for ink mismatch detection," in *12th ICDAR*, pp. 877–881, 2013.

[33] Y. Li, Y. Zheng, D. Doermann, and S. Jaeger, "Script-independent text line segmentation in freestyle handwritten documents," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 8, pp. 1313–1329, 2008.

[34] G. Zhu, Y. Zheng, D. Doermann, and S. Jaeger, "Multi-scale structural saliency for signature detection," in *CVPR*, pp. 1–8, IEEE, 2007.

[35] E. Rosten and T. Drummond, "Fusing points and lines for high performance tracking," in *10th ICCV*, vol. 2, pp. 1508–1515, IEEE, 2005.

[36] A. Alahi, R. Ortiz, and P. Vandergheynst, "Freak: Fast retina keypoint," in *CVPR*, pp. 510–517, IEEE, 2012.