Hyper-spectral Analysis for Automatic Signature Extraction

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Abstract. Signatures are one of the most accessible and prevailed ways of authenticating documents. Over the last many years, a large number of signature verification systems have been reported. A common assumption in nearly all of these system is that the signatures are available readily extracted from documents. In this paper we provide a detailed literature survey on the subject and argue that pre-extracted signatures are not always available especially in forensic cases. Furthermore, we present a novel system of automatically extracting signatures from documents with the help of hyper-spectral imaging. Initial experiments reveal that the proposed idea possess great potential to form a baseline signature extraction system above whom any signature verification system can be adjuncted for signature verification.

1. Introduction

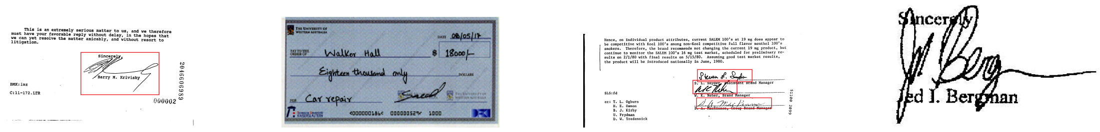
Today automatic systems facilitate us in almost every field of life. This utility varies from simple vending and ATM machines to sophisticated systems for automatically processing images and videos (Malik et al. (2013)). As the technology grew over the last few years, various systems for automatically extracting different types of information from paper document images are reported. Automatic sorting of postal mails, optical character recognition, automatic extraction of names, addresses, numbers, dates from document images, etc., are to name a few. Once extracted, each piece of information can be used for various purposes including authentication of documents.

Signatures are a widely prevailed modality used for authentication in different sectors from banking and financial institutions to forensic departments around the world. Over the last four decades a large number of offline (using only spatial information, e.g., scanned signature images) and online (using both spatial and temporal/dynamic information of signatures) signature verification systems have been reported. In almost all of these systems a common assumption is that the signatures will be always available in a form where these systems can be applied directly. Accordingly, such signature verification systems are trained (during development) and tested (during evaluation) on signatures that are already extracted from documents (usually manual extraction is performed– before or after taking the image of signatures/documents). Moreover, publicly available signature datasets also contain only pre-extracted signatures(Ahmed et al. (2012)). We, however, note that in the real world scenario, e.g., in bank checks, wills, pay slips, invoices, and contracts, etc., signatures are available along with other diverse information, such as background text, tables, stamps, and logos, etc.

Considering this, the state-of-the-art signature identification and verification systems cannot be used, as is, in realistic scenarios. In this paper we focus on the challenges which must be handled in order to develop fully automatic document analysis system capable of first extracting important information, such as signatures, from documents and then performing operations like identification and/or verification. Furthermore, we present our novel idea of automatically extracting signatures from documents with the help of hyper-spectral imaging (HSI). For our experiments, we have developed a novel HSI document dataset containing non-overlapping as well as overlapping signatures with background text, tables, stamps, and sometimes logos. The experiments prove our idea of using HSI for automatic signature extraction from documents very succcessful and we report the results of the same in this paper.

2. State-of-the-Art Information Extarction Systems

Extraction of signatures from document images has not been considered by many researchers. However, segmentation/separation of handwritten text from printed text using neural networks, Hidden Markov Models (HMM), Trained Fisher classifier, and Markov Random Fields have been reported (Guo and Ma (2001); Imade, Tatsuta and Wada (1993); Kuhnke, Simoncini and Kovacs-V (1995); Zheng, Li and Doermann (2004); Chanda, Franke and Pal (2010)). Specific methods for extraction of signatures from bank checks based on filiformity criteria and prior knowledge of Cartesian coordinate space have also been reported (Djeziri, Nouboud and Plamondon (1998); Madasu et al. (2003); Sankari, Benazir and Bremananth (2010)). Many documents other than bank checks also contain signatures. A public dataset, namely Tobacco-800, consisting of complex document images containing patch level information for 900



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

Figure 1. (a), (b), (c) Signatures at different positions in document images, (d) Signature overlapping with text

signatures along with other information is available (Zhu et al. (2007)). Zhu et al. (2007); Mandal, Roy and Pal (2011); Ahmed et al. (2012) have reported methods based on saliency map, conditional random fields, and SURF, respectively, for segmenting signatures from complete documents from subsets of Tobacco-800 dataset. These approaches segment signatures on patch level (in the form of block containing signatures and background), but fail in the cases where machine printed text touches signatures (Mandal, Roy and Pal (2011); Ahmed et al. (2012)). Some commercial systems capable of finding one or two signatures in bank checks and IRD snippets and later apply signature verification are available, e.g., SignatureXpert-2 [1] by Parascript.

To the best of authors' knowledge, no method of automatic signature extraction from document images using HSI is reported in the literature. Therefore, we provide an overview of the existing automatic methods available for general hyper-spectral document image analysis. Shiel, Rehbein and Keating (2009); Aalderink et al. (2009) applied to perform quality text recovery, segmentation, and dating of historical documents from the 16th and 19th centuries based on the distribution of different types of ink and identification of corrosion. D. Goltz et al. Goltz et al. (2010) used HSI for assessing of stains, in terms of number of pixels, on the surface of historical documents. HSI is also applied for automatic forgery detection in documents based on different inks, particularly, red, blue, and black gel inks and in combination with the Fourier transform spectroscopy (Khan, Shafait and Mian (2013); Morales et al. (2014); Silva et al. (2014); Reed et al. (2014); Brauns and Dyer (2006)).

3. Hyper-spectral Imaging for Automatic Signature Extraction

We have developed a dataset containing patches from 100 document images, scanned using hyper-spectral camera with a very high spectral resolution of 2.1 nm. In addition to a high spectral resolution, this camera covers the complete visible region and infrared region (upto 900 nm). The image scanned using this hyper-spectral camera has 240 bands. The acquired data contain non overlapping, partially overlapping and completely overlapping signatures with stamps, machine printed text, tables, and logos. Bounding boxes (rectangular boxes containing signatures and overlapping objects if any within the bounds of signatures) are provided as ground truth in every case.

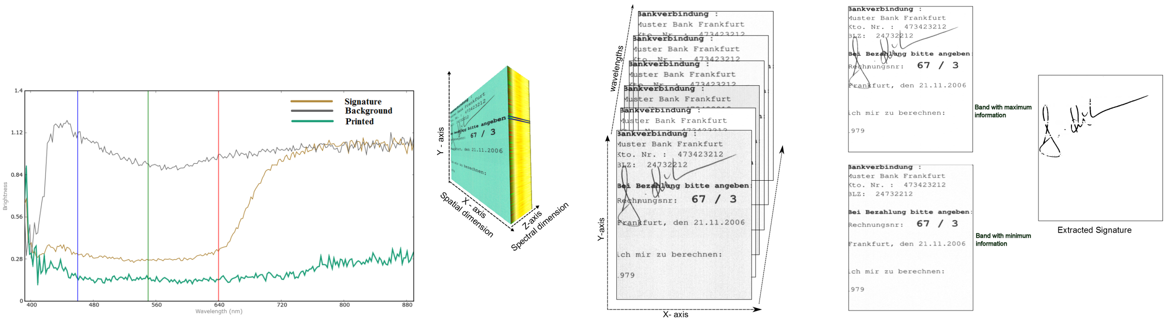
We propose the idea of applying part-based keypoint detection method (e.g., SURF) in conjunction with hyper-spectral imaging for automatic signature extraction from document images. As we scanned the documents using a hyper-spectral camera having 240 bands, each pixel has 240 values. Our analysis reveals that printers' inks have significant responses on almost all of the 240 band. While the pens' inks have significant response on some layers but little or no response on the others (different pens had different responses, but all of them disppeared on some layers of HSI). This can be seen in Figure 2 (a) where spectral responses of background, printed text, and signature pixel are shown. This observations serves as a building block for our methodology. Based on this observation, we first find the band where all the content of a document (including signature) has significant response, and then the band where signature has minimal or preferably no response. To find these bands we apply the SURF keypoint detector and count the total number of keypoints on each band, this enables us find the band with maximum number of keypoints (the band that contains the signature plus nearly all the background) and the band with the minimum number of keypoints (the band that contains potentially only signature). Once we get the two bands, we perform noise removal and morphological operations and finally subtract the band without signatures from the one with the signatures, thereby leaving us with the signatures.

Figure 2 (b) shows an example of what we actually get by applying our approach. This is infact the actual result we got on one of the documents. Note that the said approach is fully automatic and does not require human intervention at any step. Once signatures are extracted, any signature verification system can be applied or even a forensic expert can perform comparison experiments later on.

Our experiments on a set of 100 HSI scanned documents achieved the results given in Table 1. The following standard measures are used to report the system performance.

- Precision: the measure which represents that out of the total retrieved signature bounding boxes (an overlap of more than 50% marks a true positive), how many actually contain signatures.

[1] http://www.parascript.com/recognition-products/forms-processing/signaturexpert-2



(a) (b)

Figure 2. (a) Spectral Response: Background, Printed, and Signature pixels. (b) Signature Segmentation: Methodology.

- Recall: the measure which represents if the system has retrieved all the signatures from a document.

Table 1. Signature Segmentation results

Metric	Value%
Precision	100
Recall	73

4. Open Issues and Ongoing Research

We have presented the state-of-the-art of automatic information extraction methods (particularly, for signatures) from document images. Most of the today's automatic signature verification systems can not be applied directly for document authentication in the real world scenarios. This is because in such scenarios signatures are mostly available on documents, e.g., bank checks, forms, and wills, etc., with other information like, background text, lines, and logos. We argue that to perform verification in the real world especially forensic cases, first segmentation of signatures is required. Further, signatures can be found at different locations in different documents (as shown in Figure 1). Therefore, a layout free extraction of signatures is needed (as proposed in the above section). Such systems would find signatures without using priori information about the layout of the document under examination and/or probable location of signatures.

In order to have good segmentation systems that are integrable with signature verification system so that to be effectively usable in real world, it is a must to first have some benchmark datasets. These datasets would then be used to evaluate newly proposed and existing signature segmentation system in terms of their precision and recall as well as performance and quality of extraction. As mentioned earlier, we are already working on development of such a dataset and so far have developed a dataset of 100 HSI scanned documents. Currently this data has patch level information about where signatures are located, we plan to provide signature stroke information and that would be usable for testing complete signature segmentation and verification frameworks for analysis of documents containing signatures.

An improvement in the current signature verification systems can be to enable them distinguish genuine and forged signatures even in the presence of some noise in signature, e.g., touching characters or missing part of signatures (as appeared in the proposed technique). Figure 1 (d) shows a very common scenario where most of the existing signature systems will misclassify these signatures as forgery, as they assume that questioned signatures contain no information other than signatures.

Finally, the use of local features has already shown promising results in signature verification where verification is performed on the basis of parts of signatures rather than considering the complete structure of signature (Liwicki and Malik (2011)). It is assumed, in general, that the systems with local features have potential to perform well in presence of noise due to segmentation or background and therefore should be integrable with signature segmentation systems.

References

Aalderink, B., M. Klein, R. Padoan, G. De Bruin and T. Steemers. 2009. Clearing the Image: A Quantitative Analysis of Historical Documents Using Hyperspectral Measurements. In *37th AIC*.

Ahmed, Sheraz, Muhammad Imran Malik, Marcus Liwicki and Andreas Dengel. 2012. Signature Segmentation from Document Images. In *ICFHR*. IEEE. 423-427.

Banerjee, Purnendu and Bidyut Baran Chaudhuri. 2012. A System for Hand-Written and Machine-Printed Text Separation in Bangla Document Images. In *ICFHR*. IEEE.

Brauns, Eric B and R Brian Dyer. 2006. "Fourier transform hyperspectral visible imaging and the nondestructive analysis of potentially fraudulent documents." *Applied spectroscopy* 60(8):833–840.

Chanda, Sukalpa, Katrin Franke and Umapada Pal. 2010. Structural handwritten and machine print classification for sparse content and arbitrary oriented document fragments. In *ACM-SAC*. pp. 18–22.

Djeziri, S., F. Nouboud and R. Plamondon. 1998. "Extraction of signatures from check background based on a filiformity criterion." *TIP* 7(10):1425–1438.

Goltz, Douglas, Michael Attas, Gregory Young, Edward Cloutis and Maria Bedynski. 2010. "Assessing stains on historical documents using hyperspectral imaging." *Journal of Cultural Heritage* 11(1):19–26.

Guo, J.K. and M.Y. Ma. 2001. Separating handwritten material from machine printed text using hidden Markov models. In *ICDAR*. pp. 439 –443.

Hunt, Robert William Gainer. 2005. *The reproduction of colour*. John Wiley & Sons.

Imade, S., S. Tatsuta and T. Wada. 1993. Segmentation and classification for mixed text/image documents using neural network. In *ICDAR*. pp. 930 –934.

Jayadevan, R., S.R. Kolhe, P.M. Patil and U. Pal. 2012. "Automatic processing of handwritten bank cheque images: a survey." *IJDAR* 15:267–296.

Khan, Z., F. Shafait and A. Mian. 2013. Hyperspectral Imaging for Ink Mismatch Detection. In *ICDAR*. pp. 877–881.

Kuhnke, K., L. Simoncini and Zs.M. Kovacs-V. 1995. A system for machine-written and hand-written character distinction. In *ICDAR*. Vol. 2 pp. 811 –814 vol.2.

Leutenegger, Stefan, Margarita Chli and Roland Yves Siegwart. 2011. BRISK: Binary robust invariant scalable keypoints. In *ICCV*. IEEE pp. 2548–2555.

Liwicki, Marcus and Muhammad Imran Malik. 2011. Surprising? Power of Local Features for Automated Signature Verification. In *IGS*. pp. 18–21.

Lowe, D.G. 1999. Object recognition from local scale-invariant features. In *ICCV*. pp. 1150–1157.

Madasu, Vamsi Krishna, Mohd Hafizuddin, Mohd Yusof, M. Hanm and Lu Ss. 2003. Automatic extraction of signatures from bank cheques and other documents. In *DICTA*. pp. 591–600.

Malik, M. I., Marcus Liwicki, Andreas Dengel and Bryan Found. 2013. Man vs. Machine: A Comparative Analysis for Forensic Signature Verification. In *IGS*. International Graphonomics Society pp. 9–13.

Malik, Muhammad Imran, Marcus Liwicki and Andreas Dengel. 2013. Part-based automatic system in comparison to human experts for forensic signature verification. In *ICDAR*. IEEE pp. 872–876.

Mandal, Ranju, Partha Pratim Roy and Umapada Pal. 2011. "Signature Segmentation from Machine Printed Documents Using Conditional Random Field." *ICDAR* 0:1170–1174.

Mandal, Ranju, Partha Pratim Roy and Umapada Pal. 2012. "Signature Segmentation From Machine Printed Documents Using Contextual Information." *IJPRAI* .

Morales, A., M. Ferrer, M. Diaz-Cabrera, C. Carmona and G. Thomas. 2014. The use of hyperspectral analysis for ink identification in handwritten documents. In *ICCST*. IEEE pp. 1–5.

Mozaffari, Saeed and Parnia Bahar. 2012. Farsi/Arabic Handwritten from Machine-printed Words Discrimination. In *ICFHR*. IEEE.

Reed, G, K Savage, D Edwards and N Nic Daeid. 2014. "Hyperspectral imaging of gel pen inks: An emerging tool in document analysis." *Science & Justice* 54(1):71–80.

Rosten, Edward and Tom Drummond. 2005. Fusing points and lines for high performance tracking. In *ICCV*. Vol. 2 pp. 1508–1515 Vol. 2.

Sankari, M., M. Benazir and R. Bremananth. 2010. Verification of bank cheque images using Hamming measures. In *ICARCV 10*. pp. 2531 –2536.

Shiel, P., M. Rehbein and J. Keating. 2009. "The ghost in the manuscript: Hyperspectral text recovery and segmentation." *Codicology and Palaeography in the Digital Age* pp. 159–174.

Silva, C., M. Pimentel, R. Honorato, C. Pasquini, J. Prats-Montalbán and A. Ferrer. 2014. "Near infrared hyperspectral imaging for forensic analysis of document forgery." *Analyst* 139(20):5176–5184.

Wyszecki, G and WS Stiles. 1982. "Color science: Concepts and methods, quantitative data and formulae. 1982." *John Wiley&Sons, New York* .

Zheng, Yefeng, Huiping Li and D. Doermann. 2004. "Machine printed text and handwriting identification in noisy document images." *TPAMI* 26(3):337 –353.

Zhu, Guangyu, Yefeng Zheng, David Doermann and Stefan Jaeger. 2007. *Multi-scale Structural Saliency for Signature Detection*. Minneapolis, MN pp. 1 – 8.

Zhu, Guangyu, Yefeng Zheng, David Doermann and Stefan Jaeger. 2009. "Signature Detection and Matching for Document Image Retrieval." *TPAMI* 31(11):2015–2031.