# Towards Automated Hyperspectral Document Image Analysis

Zohaib Khan, Faisal Shafait and Ajmal Mian
School of Computer Science and Software Engineering
The University of Western Australia, 35 Stirling Highway, CRAWLEY, 6009
Email: zohaib@csse.uwa.edu.au, faisal.shafait@uwa.edu.au, ajmal.mian@uwa.edu.au

***Abstract*—Hyperspectral imaging and analysis refers to the capture and understanding of image content in multiple spectral channels. Satellite and airborne hyperspectral imaging has been the focus of research in remote sensing applications since nearly the past three decades. Recent use of ground-based hyperspectral imaging has found immense interest in areas such as medical imaging, art and archaeology, and computer vision. In this paper, we make an attempt to draw closer the forensic community and image analysis community towards automated forensic document examination. We believe that it has a huge potential to solve various challenging document image analysis problems, especially in the forensic document examination domain. We present the use of hyperspectral imaging for ink mismatch detection in handwritten notes as a sample application. Overall, this paper provides an overview of the applications of hyperspectral imaging with focus on solving pattern recognition problems. We hope that this work will pave the way for exploring its true potential in the document analysis research field.**

***Keywords*—Multispectral imaging, Hyperspectral imaging, Hyperspectral document analysis, forensic document examination, ink mismatch detection***

## I. Introduction

Human eye exhibits a trichromatic vision. This is due to the presence of three types of photo-receptors called *Cones* that are sensitive to different wavelength ranges in the visible range of the electromagnetic spectrum [1]. Conventional imaging sensors and displays (like cameras, scanners and monitors) are developed to match the response of the trichromatic human vision so that they deliver the same perception of the image as in a real scene. This is why an RGB image constitutes three spectral measurements per pixel. Most of the computer vision applications do not make use of the spectral information and directly employ grayscale images for image understanding. There is evidence that machine vision tasks can take the advantage of image acquisition in a wider range of electromagnetic spectrum capturing more information in a scene compared to only RGB data. Hyperspectral imaging captures spectral reflectance information for each pixel in a wide spectral range. It also provides selectivity in the choice of frequency bands. Satellite based hyperspectral imaging sensors have long been used for astronomical and remote sensing applications. Due to the high cost and complexity of these hyperspectral imaging sensors, various techniques have been proposed in the literature to utilize conventional imaging systems combined with a few off-the-shelf optical devices for hyperspectral imaging.

Strictly speaking, an RGB image is a three channel multispectral image. An image acquired at more than three specific wavelengths in a band is referred to as a *Multispectral Image*. Generally, multispectral imaging sensors acquire more than three spectral bands. An image with a higher spectral resolution or more number of bands is regarded as a *Hyperspectral Image*. There is no clear demarcation with regards to the number of spectral bands/resolution between multispectral and hyperspectral images. However, hyperspectral sensors may acquire a few dozen to several hundred spectral measurements per scene point. For example, the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) of NASA has 224 bands in 400-2500nm range [2].

During the past several years hyperspectral imaging has found its utility in various ground-based applications. The use of hyperspectral imaging in archeological artifacts restoration has shown promising results. It is now possible to read the old illegible historical manuscripts by restoration using hyperspectral imaging [3]. This was a fairly difficult task for a naked eye due to its limited capability, restricted to the visible spectral range. Similarly, hyperspectral imaging has also been applied to the task of material discrimination. This is because of the physical property of a material to reflect a specific range of wavelengths giving it a spectral signature which can be used for material identification [4]. The greatest advantage of hyperspectral imaging in such applications is that it is non-invasive and thus does not affect the material under analysis compared to other invasive techniques which inherently affect the material under observation.

Despite the success of hyperspectral imaging in solving various challenging computer vision problems in recent years, its use in the document image analysis research has remained largely unexplored. In this paper, we intend to draw the attention of the document analysis and forensics community towards this promising technology. We believe that there is a huge potential in hyperspectral imaging to solve various challenging document image analysis problems, especially in the forensic document examination domain. First, we present in Section II a brief survey on the applications of hyperspectral imaging in the field of pattern recognition. Then, some of our recent work on forensic document examination using hyperspectral imaging is discussed in Section III. The paper is concluded with some hints about directions for future research in Section IV.

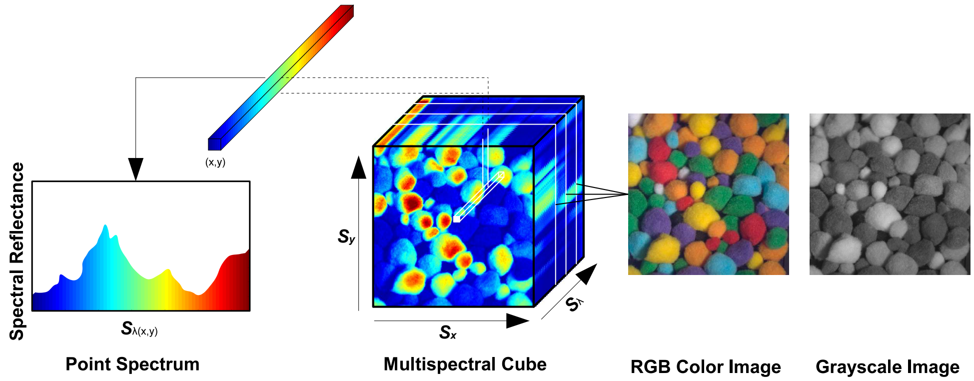


Fig. 1. A hyperspectral image is represented as a 3D cube (shown in pseudo-colors in center). Each slice of the cube along the spectral dimension $S_\lambda$ is regarded as a channel or a band. Point spectrum on the spectral cube at the $(x, y)$ spatial location (left). An RGB image and a grayscale image rendered from the hyperspectral cube (right).

## II. Hyperspectral Imaging and Applications

A hyperspectral image has three dimensions: two spatial ($S_x$ and $S_y$) and one spectral ($S_\lambda$) (see Figure 1). The hyperspectral data can be represented in the form of a *Spectral Cube*. Similarly, a hyperspectral video has four dimensions – two spatial dimensions ($S_x$ and $S_y$), a spectral dimension ($S_\lambda$) and a temporal dimension ($t$). The hyperspectral video can be thought of as a series of *Spectral Cubes* along temporal dimension. Hyperspectral imaging has been applied in various areas, some of which are listed in Table I. In the following, we provide a brief survey of the applications of hyperspectral imaging in pattern recognition. The scope of our survey is limited to the multispectral and hyperspectral imaging systems used in ground-based computer vision applications. Therefore, high cost and complex sensors for remote sensing, astronomy, and other geo-spatial applications are excluded from the discussion.

TABLE I. Applications of hyperspectral imaging in different areas.

| Areas | Applications |
|---|---|
| Art and Archeology | Analysis of works of art, historical artifact restoration |
| Medical Imaging | MRI imaging, microscopy, biotechnology |
| Military | Surveillance, access control |
| Pattern Recognition | Material identification, biometrics |
| Remote Sensing | Crop monitoring, mineralogy, water observation |

### A. Biometrics Applications

The bulk of biometric recognition research revolves around monochromatic imaging. Recently, different biometric modalities have taken advantage of hyperspectral imaging for reliable and improved recognition. The images can cover visible, infrared, or a combination of both ranges of the electromagnetic spectrum (see Figure 2). We briefly discuss the recent work in palmprint, face, fingerprint, and iris recognition using hyperspectral imaging.

Palmprints have emerged as a popular choice for human access control and identification. Interestingly, palmprints have even more to offer when imaged under different spectral ranges. The line pattern is captured in the visible range while the vein pattern becomes apparent in the near infrared range. Both line and vein information can be captured using a multispectral imaging system such as those developed by Han et al. [5] or Hao et al. [6]. The underlying principle of a multispectral palmprint imaging device is to use a monochromatic camera with illumination sources of different colors. Images of a palm are sequentially captured under each illumination within a fraction of a second.

Multispectral palmprint recognition system of Han et al. [5] captured images under four different illuminations (red, green, blue and infrared). The first two bands (blue and green) generally showed only the line structure, the red band showed both line and vein structures, whereas the infrared band showed only the vein structure. These images can be fused and features extracted for subsequent matching and recognition. The contact-free imaging system of Hao et al. [6] acquires multispectral images of a palm under six different illuminations. The contact-free nature of the system offers more user acceptability while maintaining a reasonable accuracy. Experiments show that pixel level fusion of multispectral palmprints has better recognition performance compared to monochromatic images. The accuracy achievable by multispectral palmprints is much higher compared to traditional monochromatic systems.

Fingerprints are established as one of the most reliable biometrics and are in common use around the world. Fingerprints can yield even more robust features when captured under a multispectral sensor. Rowe et al. [7] developed a multispectral imaging sensor for fingerprint imaging. The system comprised of illumination source of multiple wavelengths (400, 445, 500, 574, 610 and 660nm) and a monochrome CCD of 640x480 resolution. They showed that MSI sensors are less affected by moisture content of skin which is of critical significance compared to the traditional sensors. Recognition based on multispectral fingerprints outperformed standard fingerprint imaging.

Face recognition has an immense value in human identification and surveillance. The spectral response of human skin is a distinct feature which is largely invariant to the pose and expression [8] variation. Moreover, multispectral images of faces are less susceptible to variations in illumination sources and their directions [9]. Multispectral face recognition systems generally use a monochromatic camera coupled with a *Liquid Crystal Tunable Filter* (LCTF) in the visible and/or near-infrared range. A multispectral image is captured by electronically tuning the filter to the desired wavelengths and acquiring images in a sequence.

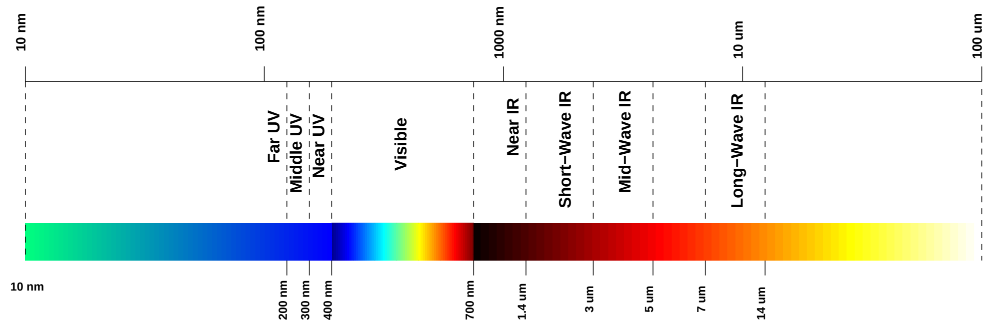


Fig. 2. The electromagnetic spectrum.

Iris is another unique biometric used for person authentication. Boyce et al. [10] explored multispectral iris imaging in the visible electromagnetic spectrum and compared it to the near-infrared in a conventional iris imaging systems. The use of multispectral information for iris enhancement and segmentation resulted in improved recognition performance.

### *B. Material Identification*

Naturally existing materials show a characteristic spectral response to incident light. This property of a material can distinguish it from other materials. The use of multispectral techniques for imaging the works of arts like paintings allows segmentation and classification of painted parts. This is based on the pigment physical properties and their chemical composition [3]. Pelagotti et al. [11] used multispectral imaging for analysis of paintings. They collected multispectral images of a painting in UV, Visible and Near IR band. It was possible to differentiate among different color pigments which appear similar to the naked eye based on spectral reflectance information.

Gregoris et al. [12] exploited the characteristic reflectance of ice in the infrared band to detect ice on various surfaces which is difficult to inspect manually. The developed prototype called *MD Robotics' Spectral Camera system* could determine the type, level and location of the ice contamination on a surface. The prototype system was able to estimate thickness of ice ($<$0.5mm) in relation to the measured spectral contrast. Such system may be of good utility for aircraft/space shuttle ice contamination inspection and road condition monitoring in snow conditions.

Multispectral imaging has critical importance in magnetic resonance imaging. Multispectral magnetic resonance imagery of brain is in wide use in medical science. Various tissue types of the brain are distinguishable by virtue of multispectral imaging which aids in medical diagnosis [13].

Clemmensen et al. [14] used multispectral imaging to estimate the moisture content of sand used in concrete. It is a very useful technique for non-destructive in-vivo examination of freshly laid concrete. A total of nine spectral bands was acquired in both visual and near infrared range. Zawada et al. [15] proposed a novel underwater multispectral imaging system named *LUMIS* (Low light level Underwater Multispectral Imaging System) and demonstrated its use in study of phytoplankton and bleaching experiments.

Spectrometry techniques are also widely used to identify the fat content in pork meat, because it has proved significantly cheaper and more efficient than traditional analytical chemistry methods [16]. For that purpose, near-infrared spectrometers are used that measure the spectrum of light transmitted through a sample of minced pork meat.

Last but not least, multispectral imaging has also important applications in defense and security. For instance, Alouini [17] showed that multispectral polarimetric imaging significantly enhances the performance of target detection and discrimination.

## III. Forensic Document Examination using Hyperspectral Imaging

Hyperspectral imaging (HSI) has recently emerged as an efficient non-destructive tool for detection, enhancement [18], comparison and identification of forensic traces [19]. Such systems have a huge potential for aiding forensic document examiners in various tasks. Brauns et al. [20] developed a hyperspectral imaging system to detect forgery in potentially fraudulent documents in a non-destructive manner. A more sophisticated hyperspectral imaging system was developed at the National Archives of Netherlands for the analysis of historical documents in archives and libraries [21]. The system provided high spatial and spectral resolution from near-UV through visible to near IR range. The only limitation of the system was its extremely slow acquisition time (about 15 minutes) [22]. Other commercial hyperspectral imaging systems from Foster & Freeman [23] and ChemImage [24] also allow manual comparison of writing ink samples. Hammond [25] used visual comparison in Lab color mode for differentiating different black inks. Such manual analysis of inks cannot establish the presence of different inks with certainty, because of inherent human error. Here we will demonstrate a promising application of hyper-spectral imaging for automated writing inks mismatch detection that we have recently proposed [26]. The work is based on the assumption that same inks exhibit similar spectral responses whereas different inks show dissimilarity in their spectra. The phenomenon is illustrated in Figure 3. We assume that the spectral responses of the inks are independent of the writing styles of different subjects.

Using our hyperspectral imaging setup (see [26] for details), a database comprising of 70 hyperspectral images of a hand-written note in 10 different inks by 7 subjects was collected[1]. All subjects were instructed to write the same sentence, once in each ink on a white paper. The pens included

[1]UWA Writing Ink Hyperspectral Image Database
http://www.csse.uwa.edu.au/%7Eajmal/databases.html

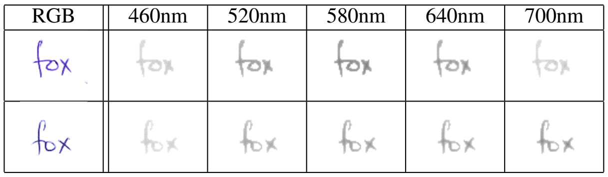


Fig. 3. The above images highlight the discrimination of inks offered by hyperspectral images. We show a selected number of bands at specific wavelengths for two different blue inks (for the word 'fox'). Notice that only the pixels belonging to the writing pixels are shown and the pixels of the background are masked out. A closer look allows one to appreciate that hyperspectral imaging captures subtle differences in the inks, which are enhanced, especially at higher wavelengths.

5 varieties of blue ink and 5 varieties of blank ink pens. It was ensured that the pens came from different manufacturers while the inks still appeared visually similar. Then, we produced mixed writing ink images from single ink notes by joining equally sized image portions from two inks written by the same subject. This made roughly the same proportion of the two inks under question.

The mixed-ink images were pre-processed (binarization [27] followed by spectral response normalization) and then fed to the $k$-means clustering algorithm with a fixed value of $k = 2$. Finally, based on the output of clustering, segmentation accuracy was computed as

$$\text{Accuracy} = \frac{\text{True Positives}}{\text{True Positives + False Positives + False Negatives}}$$

The segmentation accuracy is averaged over seven samples for each ink combination $C_{ij}$. It is important to note that according to this evaluation metric, the accuracy of a random guess (in a two class problem) will be 1/3. This is different from common classification accuracy metrics where the accuracy of a random guess is 1/2. This is because our chosen metric additionally penalizes false negatives which are useful to quantify in a segmentation problem.

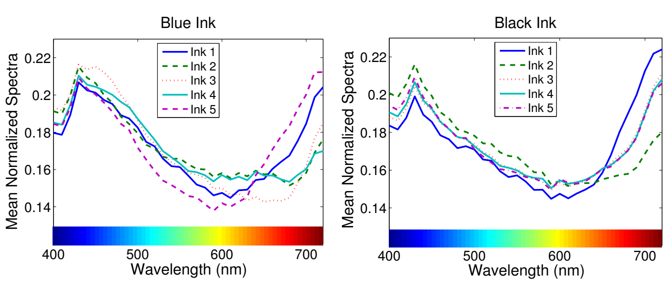


Fig. 4. Spectra of the blue and black inks under analysis. Note that at some ranges the ink spectra are more distinguished than others.

Figure 4 shows the average normalized spectra of all blue and black inks, respectively. It was achieved by computing the average of the spectral responses of each ink over all samples in the database. It can be observed that the spectra of the inks are distinguished at different ranges in the visible spectrum. A close analysis of variability of the ink spectra in these ranges reveals that most of the differences are present in the high-visible range, followed by mid-visible and low-visible ranges.

We now inspect how hyperspectral information can be beneficial in discrimination of inks. We compare the segmentation accuracy of HSI with RGB in Figure 5. As expected,

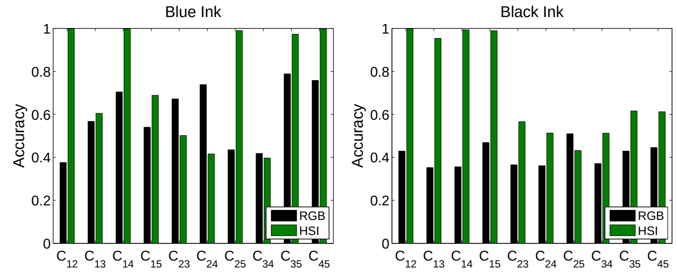


Fig. 5. Comparison of RGB and HSI image based segmentation accuracy.

HSI significantly improves over RGB in most of the ink combinations. This results in most accurate clustering of ink combinations $C_{12}$, $C_{14}$, $C_{12}$, $C_{25}$, $C_{35}$ and $C_{45}$. In case of black inks, ink 1 is highly distinguished from all other inks resulting in the most accurate clustering for all combinations $C_{1j}$. However, it can be seen that for a few combinations, HSI does not show a remarkable improvement. Instead, in some cases, it is less accurate compared to RGB. These results encouraged us to further look at HSI in detail in order to take advantage of the most informative bands. The results of different feature (band) selection methods for this problem are detailed in [26]. Overall, the results showed that use of a few selected bands further improved discrimination between most of the ink combinations.

We now present some qualitative results on segmentation of blue and black ink combinations. The original images of a combination of two blue inks ($C_{34}$) and black inks ($C_{45}$) are shown are in Figure 6. RGB images are shown here for better visual appearance. The ground truth images are labeled in pseudo-colors, where green pixels represent the first ink and red pixels represent the second ink.

The clustering based on RGB images fails to group similar ink pixels into the same clusters. A closer look reveals that all of the ink pixels are falsely grouped into one cluster, whereas most of the boundary pixels are grouped into the other cluster. This implies that typical RGB imaging is not sufficient to discriminate inks that appear visually similar to each other. On the other hand, segmentation based on HSI is much more effective compared to RGB. It can be seen that the majority of the ink pixels are correctly grouped in HSI in accordance with the ground truth segmentation. Note that the $k$-means clustering algorithm used in this work is rather basic. The use of more advance clustering algorithms has the potential of further improving the accuracy of ink segmentation.

## IV. Conclusion and Outlook

This paper presented an overview about different applications of hyperspectral imaging in pattern recognition. We also demonstrated a sample application of HSI in document image analysis, where it was possible to discriminate between two visually similar inks using hyperspectral images of the documents. This is the first reported work on using automatic document image analysis methods in combination with hyperspectral imaging to address forensically relevant issues in questioned document examination. In future, it will be interesting to see whether spectral imaging can aid in writer identification. Since it is possible to identify hand writings


Fig. 6. Example test images. For a visual comparison of RGB and HSI mismatch detection accuracy, we purposefully selected two hard cases.

by the texture [28] or ink-deposition traces [29], a promising research direction would be to investigate whether these feeble variations in ink strokes are reflected in the spectral response of the inks. In addition, ink or document aging is a phenomenon that can be observed in a more effective manner using spectral imaging. During the aging process, the chemical properties of ink and paper change due to various environmental factors. Spectral imaging can potentially capture subtle differences in inks or paper due to aging. These are just a few application examples where HSI can potentially provide solutions to some major practical problems in document analysis. We hope that this work will open up many exciting possibilities for tackling forensic document examination problems with a new perspective.

## ACKNOWLEDGMENT

This research was supported by ARC Grant DP110102399.

## REFERENCES

[1] P. R. Martin, "Retinal color vision in primates," in *Encyclopedia of Neuroscience*. Springer, 2009, pp. 3497–3501.

[2] P. Shippert, "Introduction to hyperspectral image analysis," *Online Journal of Space Communication*, vol. 3, 2003.

[3] S. Baronti, A. Casini, F. Lotti, and S. Porcinai, "Principal component analysis of visible and near-infrared multispectral images of works of art," *Chemometrics and Intelligent Laboratory Systems*, vol. 39, no. 1, pp. 103–114, 1997.

[4] B. Thai and G. Healey, "Invariant subpixel material detection in hyperspectral imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 40, no. 3, pp. 599–608, 2002.

[5] D. Han, Z. Guo, and D. Zhang, "Multispectral palmprint recognition using wavelet-based image fusion," in *Proc. International Conference on Signal Processing*. IEEE, 2008, pp. 2074–2077.

[6] Y. Hao, Z. Sun, T. Tan, and C. Ren, "Multispectral palm image fusion for accurate contact-free palmprint recognition," in *Proc. International Conference on Image Processing*. IEEE, 2008, pp. 281–284.

[7] R. K. Rowe, K. Nixon, and S. Corcoran, "Multispectral fingerprint biometrics," in *Proc. IEEE SMC Information Assurance Workshop*. IEEE, 2005, pp. 14–20.

[8] Z. Pan, G. Healey, M. Prasad, and B. Tromberg, "Face recognition in hyperspectral images," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1552–1560, 2003.

[9] H. Chang, A. Koschan, M. Abidi, S. G. Kong, and C.-H. Won, "Multispectral visible and infrared imaging for face recognition," in *Proc. Computer Vision and Pattern Recognition Workshops*. IEEE, 2008, pp. 1–6.

[10] C. Boyce, A. Ross, M. Monaco, L. Hornak, and X. Li, "Multispectral iris analysis: A preliminary study," in *Proc. Computer Vision and Pattern Recognition Workshops (CVPRW)*. IEEE, 2006.

[11] A. Pelagotti, A. Del Mastio, A. De Rosa, and A. Piva, "Multispectral imaging of paintings," *IEEE Signal Processing Magazine*, vol. 25, no. 4, pp. 27–36, 2008.

[12] D. Gregoris, S. Yu, and F. Teti, "Multispectral imaging of ice," in *Proc. Canadian Conference on Electrical and Computer Engineering*, vol. 4. IEEE, 2004, pp. 2051–2056.

[13] T. Taxt and A. Lundervold, "Multispectral analysis of the brain using magnetic resonance imaging," *IEEE Transactions on Medical Imaging*, vol. 13, no. 3, pp. 470–481, 1994.

[14] L. H. Clemmensen, M. E. Hansen, and B. K. Ersbøll, "A comparison of dimension reduction methods with application to multi-spectral images of sand used in concrete," *Machine Vision and Applications*, vol. 21, no. 6, pp. 959–968, 2010.

[15] D. G. Zawada, "Image processing of underwater multispectral imagery," *IEEE Journal of Oceanic Engineering*, vol. 28, no. 4, pp. 583–594, 2003.

[16] H. H. Thodberg, "A review of bayesian neural networks with an application to near infrared spectroscopy," *IEEE Transactions on Neural Networks*, vol. 7, no. 1, pp. 56–72, 1996.

[17] M. Alouini, "Target detection and discrimination through active multispectral polarimetric imaging," in *Computational Optical Sensing and Imaging*. Optical Society of America, 2005, pp. 1–8.

[18] S. Joo 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.

[19] G. Edelman, E. Gaston, T. van Leeuwen, P. Cullen, and M. Aalders, "Hyperspectral imaging for non-contact analysis of forensic traces," *Forensic Science International*, vol. 223, pp. 28–39, 2012.

[20] E. B. Brauns and R. B. Dyer, "Fourier transform hyperspectral visible imaging and the nondestructive analysis of potentially fraudulent documents," *Applied spectroscopy*, vol. 60, no. 8, pp. 833–840, 2006.

[21] 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.

[22] M. E. Klein, B. J. Aalderink, R. Padoan, G. De Bruin, and T. A. Steemers, "Quantitative hyperspectral reflectance imaging," *Sensors*, vol. 8, no. 9, pp. 5576–5618, 2008.

[23] foster + freeman, http://www.fosterfreeman.com/index.php.

[24] ChemImage, http://www.chemimage.com/.

[25] D. L. Hammond, "Validation of lab color mode as a nondestructive method to differentiate black ballpoint pen inks*," *Journal of forensic sciences*, vol. 52, no. 4, pp. 967–973, 2007.

[26] Z. Khan, F. Shafait, and A. Mian, "Hyperspectral imaging for ink mismatch detection," in *Proc. International Conference on Document Analysis and Recognition (ICDAR)*, 2013.

[27] F. Shafait, D. Keysers, and T. M. Breuel, "Efficient implementation of local adaptive thresholding techniques using integral images," *Document Recognition and Retrieval XV*, pp. 681 510–681 510–6, 2008.

[28] K. Franke, O. Bunnemeyer, and T. Sy, "Ink texture analysis for writer identification," in *Proc. IEEE Workshop on Frontiers in Handwriting Recognition*, 2002, pp. 268–273.

[29] K. Franke and S. Rose, "Ink-deposition model: The relation of writing and ink deposition processes," in *Proc. IEEE Workshop on Frontiers in Handwriting Recognition*, 2004, pp. 173–178.