

## QUALITY IMPROVEMENT OF MULTISPECTRAL IMAGES FOR ANCIENT DOCUMENTS ANALYSIS

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### ABSTRACT:

Multispectral imaging is widely used for the analysis of ancient documents, like manuscripts or printed books, affected over time by degradations. Document digitization is performed with a monochrome sensor (CCD or CMOS) and an optical filter for each spectral band (infrared, visible, ultraviolet). This allows to capture additional information with respect to common RGB imaging, revealing details invisible to human eye. The use of optical filters causes geometrical changes and channel-dependent blurring, due to different refraction indices and manual focus setting. Moreover, document manipulations cause alterations among the channel images. Then, if the purpose of the study is the virtual restoration of the document and not only its interpretation, elaboration of the multispectral images is required. In this paper we will present a methodology, tested on individual solutions, to preliminarily register the images in order to correct geometrical misalignments, and apply deblurring techniques to improve image quality for further document analysis, where sharper images are needed. Deblurring is performed with a multichannel approach, adapted to the case of multispectral acquisition. Statistical techniques of decorrelation are applied to improve the legibility of documents or to restore degraded features, extract individual context parts of the document, separate patterns as the main text from the background, or attenuate interferences due to the seeping of ink from verso-to-recto.

### 1. INTRODUCTION

Multispectral imaging is widely used for the analysis of ancient documents (handwritten or printed) affected by several types of degradations (Tonazzini, 2004; Lettner, 2009), which could be due either to ageing, atmospheric influences, inappropriate archiving and manipulations, and to the seeping of ink from the reverse side (bleed-through) or the transparency of text through the page (show-through) (Drida, 2006). Digital acquisition in different spectral bands (infrared, visible, ultraviolet) extends the document information with respect to common RGB capture (Martinez, 1996). The acquired information changes with the spectral band. Indeed, infrared and ultraviolet channels allow hidden details to be detected (Lettner, 2008; Easton, 2003), such as underwritten text in palimpsests (i.e., manuscript pages that have been scraped off and re-used).

Different optical filters and a monochrome sensor (CCD, Charge Coupled Device, or CMOS, Complementary Metal-Oxide Semiconductor) are used in multispectral imaging for data acquisition in several spectral ranges. Because of the different refraction indices and thicknesses of the filters, the acquired images can be misaligned and affected by blur (Brauers, 2008; Mansouri, 2005). Manual focusing operations make the capture of sharp images difficult, especially in the infrared range, where the text disappears and the low-contrast background is more visible. Moreover, document manipulations (i.e. page repositioning or leafing through during the recto-verso acquisition) alter the geometry of the acquired scene. Therefore, further image analysis tasks require a registration of the multispectral images (Lettner, 2007).

Image processing techniques are necessary to analyze the content of the document, either to remove unwanted

background artifacts, to improve legibility of the main text or extract salient features, such as symbols, stamps or watermarks.

In our work we propose to align multispectral images by an automatic registration method based on the Fourier-Mellin transform (Reddy, 1996). After this preliminary step, deblurring techniques can be applied to minimize the blurring level, to improve the quality of the images and increase their suitability for contrast correction and noise removal.

Multichannel blind deconvolution (Šroubek, 2005) estimates the original (sharper) image and the Point Spread Function (PSF) from the blur convolution model:

$$\text{Image}_{\text{blurred}} = \text{convolution}(\text{Image}_{\text{original}}, \text{PSF}) + \text{noise}.$$

The method is based on the processing of several input images (multichannel) and it works *blindly*, e.g. it does not require strong a priori information about the present PSF. The resulting restored image is sharper, with less noise and blur.

So far, this technique has been applied on multiple images from the same channel, with different focal settings. We try to extend this application to several channels, as in multispectral acquisition, assuming the knowledge of the PSF that describes the blur component in the image. After registration and deconvolution, we are allowed to analyze an image with improved quality and readability, relying on the fact that corresponding pixels in the different channels carry information coming from exclusively the same spatial locations. So multispectral acquisitions can be modelled as unknown mixtures of all the patterns that overlap in the document, so that blind source separation techniques can be attempted to separate them (Tonazzini, 2004). Such a strategy can be seen as a

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particular approach for a soft segmentation of the document content, where each pixel of the digitized document may belong to different document structures (Tai, 2007).

## 2. RELATED WORK

In this Section we provide a review of the deblurring techniques that we propose to apply for the improvement of the virtual restoration of ancient documents.

Deblurring techniques, often called deconvolution methods, aim to improve the image quality in terms of removal of image blur and noise reduction. The amount of a priori information related to the degradation, such as the size or shape of the blurring functions and noise parameters, affects significantly the success of deconvolution. When the blur function is known (non-blind deconvolution), many conventional approaches have been developed to recover the sharp image (see a review in Banham, 1997).

A more challenging problem occurs when the blur is unknown (blind image deconvolution). A state-of-the-art survey of blind restoration techniques is given in Campisi (2007). Most of the methods are iterative and minimize specific functionals. They involve regularization terms based on available prior information (i.e. image characteristics which can be expected) that assures various statistical properties of the image and constrains the estimated image and/or blurs. Regularization is required to improve stability. For images with sharp changes of intensity (e.g. characters printed on paper), an appropriate regularization is based on total variation, as first introduced by Rudin (1992). Minimizing such functionals preserves edges and fine details in the image (Chan, 1998, 2000; You, 1999). Since the blind case is strongly ill-posed, all the methods suffer from convergence and stability problems. If the images are smooth and homogeneous, an autoregressive model can be used to describe the measuring process. The autoregressive model simplifies the blind problem by reducing the number of unknowns. Several techniques have been proposed to find a solution to the blind case (Lagendijk, 1990; Reeves, 1992; Haindl, 2000). One way to overcome the difficulties of single-image blind deconvolution is to use multiple acquisitions of the same scene and apply the so-called multiframe blind deconvolution (MBD) techniques.

A typical example of multiframe acquisition with a single camera is capturing several pictures of the same object with slightly different focus settings. The lack of information at one frequency provided by a single image can be supplemented by the information at the same frequency from the other images. The blind restoration problem is thus simplified by the availability of different images. Research on intrinsic multiframe methods has been started by Harikumar (1999) and Giannakis (2000). Such MBD methods overpass the limitations of previous techniques and can recover the blurring functions just from the degraded images. The MBD theory was further developed by Šroubek (2005), who proposes a noise-robust method applicable to images misaligned by unknown shifts. Šorel (2008) recently considered the very challenging problem of shift-variant blind deconvolution. The above methods have been applied to images from the same band, with different sensor settings. In our paper we are addressing the issue of multiple images, obtained using several acquisition bands, as in multispectral acquisition.

## 3. MULTISPECTRAL IMAGING

We use a multispectral camera Chroma CX3 C1600E (spectral response: 350 - 1000 nm) composed, essentially, by a monochrome CCD camera that provides gray level images with 1,6 Mpx resolution, an 8-position filter-wheel and a Nikkor 35 mm lens (Figure 1). The camera is connected to a PC with a serial interface that allows us to control image acquisition and filter shifting. An infrared filter (IR) selects the band with wavelengths between 720 nm and 880 nm. An IR cut-off filter is used to block the infrared radiation in the acquisition of visible bands (Red, Green, Blue). The image at ultraviolet (UV) wavelengths is obtained by fluorescence of UV light, in the 350 - 400 nm range. For each filter shifting, it is necessary to put the image in-focus by manually rotating the ring of the lens, since the different refractive indices of optical filters alter the FOV (Field of View) and the focal plane. An example of document acquisition in the infrared, visible and ultraviolet bands is shown in Figure 2. The ancient document is affected by stains due to ageing, and bleed-through due to seeping of ink from the reverse side. The information selectivity across the channels is apparent: in the infrared bands the foreground text disappears and hidden stamps are visible, whereas in the ultraviolet band blur and contrast increase. The focusing, manually operated, consists in capturing images and subsequently adjusting the lens, thus the image quality can be compromised by an accidental error. The acquired images can be affected by blur and geometrical misalignment due to the different filters and the manual focus setting.



Figure 1: Multispectral imaging set-up.

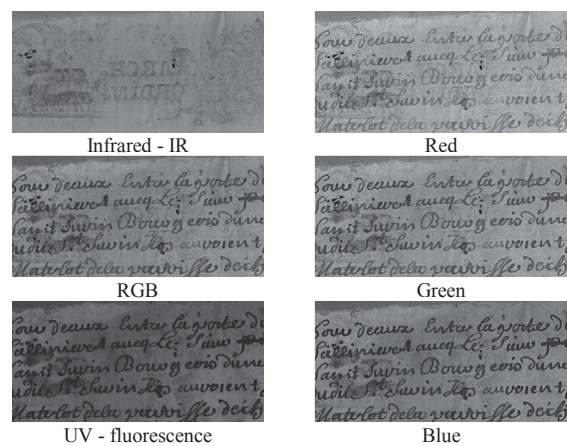


Figure 2: Document images acquired in different spectral bands.

#### 4. IMAGE REGISTRATION

Image registration represents the solution to the misalignment of the images, happening during the manual multispectral data acquisition. The multichannel data are geometrically displaced due to different optical filters and to accidental movements during the acquisition. Among the possible automatic registration methods (Zitová, 2003) we apply a method based on the Fourier-Mellin transform. An assessment of automatic registration methods applied to digital analysis of historical documents is proposed in Bianco (2008). This method provides good results for registration of recto and verso sides of a document (Tonazzini, 2009). It has a high computation speed, showing robustness against both noise and illumination conditions, and it is particularly fit for the image acquisition in different spectral ranges (assuming that there are enough common edges in the images to be registered). The whole images are used to estimate the registration parameters and match them automatically. To relate each pixel to a precise location, one of the data images is taken as a reference, and all the others are aligned to create a data cube where all the information associated to one pixel is also associated to a fixed spatial location. We suppose that the document page undergoes rigid transformations in its plane. Moreover, we take into account the changing of scale due to the different FOVs of the optical filters. Then, we can assume that a similarity transformation is sufficient to model the misalignment: once a reference image has been fixed, the other images are registered by computing the translation, rotation and scale parameters. This method applies the Fourier shift theorem to recover the translation, and a phase correlation in the log-polar domain to obtain the rotation and scale parameters (Reddy, 1996). Once all the transformations are computed, the images are cropped to let them depict the same area and have the same size. In Figure 3, an example of registration of a document is shown: the shift between the infrared and blue bands, in this case, is due to the different filters used.

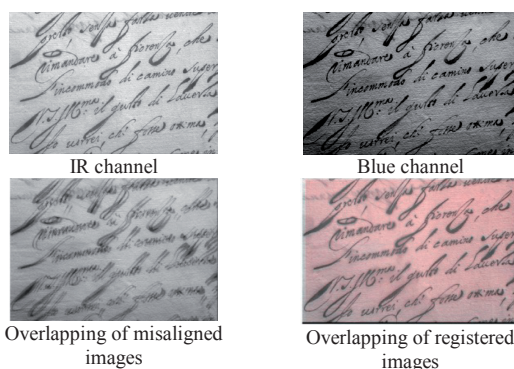


Figure 3: Registration of IR and blue channel. The overlapped data before (evidently misaligned) and after registration are shown.

#### 5. DEBLURRING

After the registration, the second problem to be tackled during the multispectral data processing is the insufficient sharpness of the acquired data. Figure 4 shows a typical example of what can happen if the camera focus is not properly set. The acquired data are then out-of-focus, blurred, and with no sharp details.

The wrong focus setting is often present due to the manual manipulation during the data acquisition, especially in the infrared channel.

This type of image degradation can be modelled by convolution with a certain unknown PSF. This PSF, which characterizes the image blur degradation, can be different for different acquisition modalities. The blurring itself and the variations of the PSF shapes for the acquired multispectral channels make further processing complicated, because the next document analysis steps suppose either no blurring or at least the same PSF for all channels. These reasons led us to introduce a deblurring step into the proposed framework. Blind deconvolution is a mathematically ill-posed problem that, however, can be regularized either if more images of the same scene are available (multiframe blind deconvolution) or by using artificial markers in the data acquisition process for PSF estimation. The latter approach is based on the fact that a blurred version of the unit pulse (Dirac delta) represents theoretically the shape of the respective PSF. Although the unit pulse is not exactly achievable, the detected shape can be used as a very good first estimate of the PSF for its further iterative improvement, performed through the deconvolution method on chosen single images. Figure 5 depicts the acquired markers with three different radii.

In theory, a smaller marker means a better representation of the PSF. However, in severely blurred images, tiny markers are hard to detect due to the limited sensitivities of the cameras, and markers cropped from the image tends to be underestimated. Still it is possible to apply iterative blind deconvolution algorithms, such as in (Campisi, 2007), and use the cropped marker as an initial estimation of the PSF. One option to improve the estimated PSF is to use bigger markers. If we know the shape of the marker and have the corresponding blurred version from the image, we can apply simple algorithms for PSF estimation (Šorel, 2009). With the estimated PSF, one can apply standard non-blind deconvolution algorithms (Campisi, 2007) with sophisticated edge-preserving regularization (Rudin, 1992), which is especially good for images of printed text. Another option to improve the PSF estimation, and thus the whole deconvolution process, is to use multiple acquisitions of the same spectral band, but with slightly different focus settings of the camera. Then we can apply MBD methods such as the ones proposed in (Šroubek, 2005).

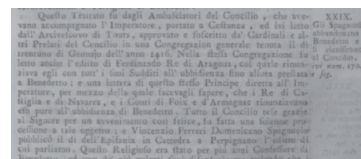


Figure 4: An example of out-of-focus blurred document image.

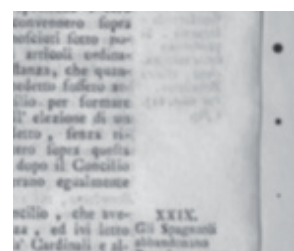


Figure 5: Artificial markers with three different radii introduced in an image. The out-of-focus blurring is apparent.



To improve the convergence speed of MBD, the cropped markers from the blurred images can be used as initial guesses of the PSFs. The disadvantage of this approach is the necessity to have at least two images in each spectral band, which slows down even further the tedious manual acquisition process. A promising method, which however must be still fully tested, would use multispectral images as individual channels in a type of semi-MBD approach. Each spectral image would be considered as a single image blind deconvolution problem with cropped markers as the initial PSFs. However, since the spectral bands are heavily correlated (e.g. edges are shared), regularization terms based on total variation have many features in common, and they can be formulated for multispectral images. A similar idea was proposed for blind deconvolution of multimodal medical images in (Šroubek, 2009). We foresee that, if properly modified, this technique can be applied to multispectral document images as well, and could represent a new direction for image deblurring.

## 6. DOCUMENT ANALYSIS

Ancient documents often appear as superpositions of different layers of information, such as the main text, additional texts coming from back-to-front interferences, spots due to ageing, and other possibly useful features such as stamps and paper watermarks. Not all the patterns may immediately be visible or identifiable.

Multispectral imaging captures a number of different channels, where some of the patterns we are interested in may be visible and distinguishable. Alternatively, one may select and compose different channels by digital image processing techniques, thus removing unwanted background artifacts or extracting salient features from the mixed information layers. The scheme in Figure 6 illustrates the process of modelling and processing, whose outputs are supposed to reproduce the unknown patterns. In Tonazzini (2004, 2007) we adopt a linear, instantaneous mixing model, with unknown coefficients, for multispectral observations, and apply successfully blind source separation techniques to recover legible recto and verso text patterns from documents affected by diverse distortions. Among our solutions we include the ICA (Independent Component Analysis) approach suggested by Hyvarinen (2000). In the linear model, it is assumed that an N-channel multispectral scan produces an N-vector  $\mathbf{x}(t)$  at each pixel  $t$ . Similarly, it is assumed that M source patterns, represented by an M-vector  $\mathbf{s}(t)$ , are superimposed to form the appearance of the document. Since we consider documents containing homogeneous texts or drawings, we can also reasonably assume that the reflectance of each undegraded source is almost uniform, and denote by  $a_{ij}$  the mean reflectance index for the  $j$ -th source at the  $i$ -th wavelength. Thus, the individual source functions  $s_i(t)$ ,  $i=1,2,\dots,M$ , denote the quantity of the M patterns that concur to form the colour at point  $t$ . It is unlikely that this simple model is able to account for the true mixing process, especially where two or more patterns overlap and the mixing becomes nonlinear (Sharma, 2001). Also, the instantaneous assumption is often not justified, since the different observation channels can be affected by different blurs. Thus, even if we want to maintain a linear model, we should at least assume convolutive mixtures with channel-specific kernels:

$$x_i(t) = h_i(t) * \sum_{j=1}^M a_{ij} s_j(t) + n_i(t) \quad (1)$$

$T = 1, 2, \dots, T$   
 $i = 1, 2, \dots, N$

where  $x_i(t)$ , and  $s_i(t)$ , are elements of  $\mathbf{x}(t)$  and  $\mathbf{s}(t)$ , respectively, and  $n_i(t)$  is the  $i$ -th channel noise at pixel  $t$ . Function  $h_i(t)$  is the blur kernel affecting channel  $i$ , and  $*$  denotes convolution. The  $N \times M$  mixing coefficients,  $a_{ij}$ , must be estimated along with the functions  $s_i(t)$  to solve the problem. Therefore, this becomes a problem of blind source separation from noisy convolutive mixtures, where the kernels  $h_i(t)$  are often known. Classical ICA for instantaneous mixtures cannot be applied to the model of eq. (1), since the kernels  $h_i(t)$  are different from a channel to another. ICA could only be applied when the blur operator is the same in every channel, i.e.,  $h_i(t)=h(t)$  for all  $i$ . The deconvolution procedure described in Section 5 aims at achieving this result even if the kernels are partially or totally unknown. To separate the sources, we can then apply a simple instantaneous ICA algorithm. Figs. 7 and 8 illustrate two examples of application of pattern separation and attenuation of degradations performed by ICA.

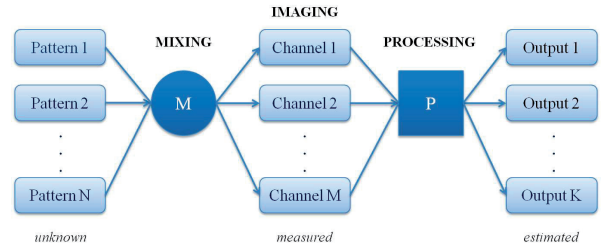


Figure 6: Superposition of different (unknown) patterns in multispectral imaging. Channel selectivity from diversity (measured) images can be translated into pattern selectivity. The outputs are estimates of the patterns.

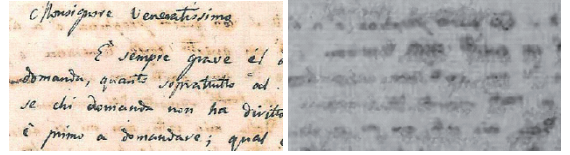


Figure 7: Recovery of bleed-through.

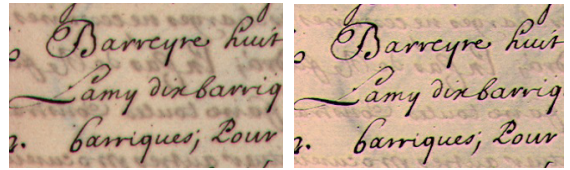


Figure 8: Attenuation of bleed-through.

## 7. CONCLUSIONS

Multispectral images can be affected by blurring due to filters with different refraction indices and to manual focus settings. We propose a methodology to deblur images acquired in different spectral bands, in order to perform a virtual restoration of ancient documents. Image sharpness is necessary to further image analysis tasks. Multichannel blind deconvolution is applied to a set of registered images of an ancient document affected by several degradations. A registration method based on the Fourier-Mellin transform allows us to compute the geometrical parameters to align the channel images to a

specified spatial reference. After registration, deconvolution techniques decrease the blurring to ease the work of further source separation methods. Here we propose a deconvolution approach that gives a preliminary estimate of the PSF through the use of artificial markers, either processing the individual images or exploiting the whole multispectral data set. In the latter case, a new semi-MBD approach will be tested, where each channel is deconvolved individually, but the total-variation regularization terms are formulated for multispectral images. Finally, statistical techniques can be applied to attenuate degradations and improve document legibility.

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