# Blending Images of Stained Glass Windows

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## Abstract

A new European collaborative research project IST-2000-28008, 'Veridical Imaging of Transmissive and Reflective Artefacts' (VITRA), has the objective to facilitate the capture of digital heritage images in historic buildings, enabling the acquisition of high quality colorimetric images of stained glass windows (SGW). One of the image processing problems that must be addressed is the mosaicing of multiple sections of a single SGW to produce a single large image. Mosaicing of SGW presents several challenges in terms of image processing. One of these is the necessity of a uniform illumination across the different parts comprising the mosaic. The observed variations are poorly compensated by global equalisation algorithms. In this paper we suggest a local approach to the problem that exploits the geometrical structure of SGW.

## Introduction

A new European collaborative research project IST-2000-28008, 'Veridical Imaging of Transmissive and Reflective Artefacts' (VITRA), has the objective to facilitate the capture of digital heritage images in historic buildings. A robotic carrier is being developed to position a high-performance digital camera plus illumination up to 15 metres above floor level, enabling the acquisition of high quality colorimetric images of stained glass windows (SGW). One of the image processing problems that must be addressed is the mosaicing of multiple sections of a single SGW to produce a single large image. This is necessitated by the degree of image detail required for conservation purposes. Spatial resolution, ideally sufficient to resolve the width of a single brush hair (tenths of a millimetre), is required in images depicting windows with dimensions of up to ten metres. In practice each 4Kx4K image from the digital camera will cover an area of about 50 cm square at a surface resolution of approximately 8 pixels per mm.

The proposed solution is to compose a mosaic of several subsections of the window, so that the available CCD resolution is consistent with these requirements. However mosaicing presents several challenges in terms of image processing. One of these is the necessity of a uniform illumination across the different parts comprising the mosaic. This can be particularly difficult to achieve with transmissive media like SGW. The illumination is normally provided by external light (direct sunlight and diffuse ambient illumination) that can change during the photographic session. Furthermore external structures, such as masonry, walls, trees and colonnades, may cast shadows onto the SGW, and these shadows may change from one mosaic tile to another depending on the changing viewpoint of the camera. This determines local variations of illumination plus a superimposed texture determined by the often irregular silhouette of the shadow. These variations are poorly compensated by global equalisation algorithms. In this paper we suggest a local approach to the problem that exploits the geometrical structure of SGW.

## Description of the problem

The problem tackled in this paper is graphically depicted in Figure 1. Two contiguous and partially overlapping sections of a SGW are shown. These sections are part of a large SGW (the "St. Frideswide window") in Christ Church Cathedral, Oxford, United Kingdom. These pictures were captured with a professional medium-format camera (Rollei 6008i) with a Jenoptik *eyelike* digital back, capable of resolutions of 3000x2000 pixels @ 16bits/channel. In this paper we assume that the camera and lens have been fully characterised in terms of geometrical and colour aberrations. In fact, this is a simplification for the sake of illustrating the proposed technique. It must

*Figure 1. Mosaicing of two SGW images:  Top section (left) bottom section (right)*

be noted, however, that the photographic parameters have been set according to factory specifications in order to guarantee the minimum degree of aberration.

The two image sections were mosaiced together using an image processing suite called Vasari Image Processing Software (VIPS) [1]. This software provides simple mosaicing features, and it is not expected to produce a perfectly seamless joint in terms of geometrical mismatch, i.e. it does not provide perspective correction capability. One may notice in Figure 1 that the joint is not perfect, but this represents a secondary issue for the sake of this paper.

A noticeable colour mismatch between the two sections is immediately evident. This is due mainly to the presence of a complex background on the exterior of the window, specifically a section of the external walls and a tree (Figure 2). The top section has been shot from a higher viewpoint, therefore the background is mainly due to the wall, which results in a fairly uniform reduction of the illumination. The bottom section has been shot from a lower viewpoint and the background includes part of the wall and foliage of the tree. This creates a complex texturisation of the illumination. For instance, the brighter, relatively isolated dots are produced by the sunlight passing through the foliage. Therefore the problem is two-fold: a localised illumination mismatch (due to the local nature of the background effect) and a texture mismatch (given by the textured illumination profile of the background).

## Description of the algorithm

This situation determines a problem that is not solvable using global equalisation techniques. Therefore the first step is to attempt a localisation of the problem. In SGW, the most intuitive form of localisation is to try to segment the individual glass

*Figure 2. Background scene outside St. Frideswide window.*

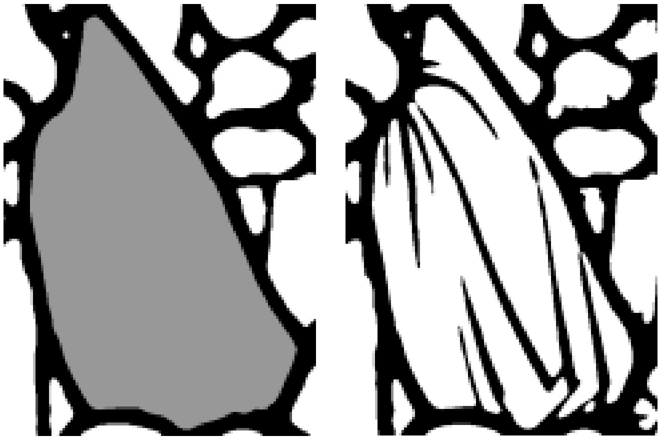

*Figure 3. Left: segmentation of the calmes with the segmented tile in grey. Right: thresholding of the painted lines (and calmes)*

patches. In a previous work [2] we have shown how it is possible to produce a satisfactory segmentation of the lead strips ("calmes") that join the individual tiles of glass in a SGW. This approach is based on a segmentation of the colour space based on a multi-layer neural network [3] classification algorithm, combined with a multi-resolution approach based on Gabor filters [4]. The technique exploits two main characteristics of the calmes, specifically their much darker colour compared to the glass tiles (dealt with by the colour space analysis), and their nearly uniform cross-sectional width (dealt with by the multi-resolution analysis). By segmenting the calmes, we are able to isolate the individual glass tiles. This constitutes the starting point for devising localised techniques. In other words, the segmentation of the calmes immediately implies the segmentation of the glass tiles as the shape delimited by the closed curve of the calme. The results of such segmentation are shown in Figure 3.

Once the individual glass tile has been isolated, we first attempt to obtain an equalisation of the average colour [5]. However the superimposed dark paint work should be removed from the computation, as it clearly constitutes an outlier of the colour distribution. From the histograms in Figure 4, one can see that the painted lines are sufficiently separated from the main mode of the colour distribution. This allows the application of automatic thresholding methods like the Otzu method [6], whose results are shown in figure. A further application of Gabor filters and morphological closing operators [7] removes isolated pixels resulting from an incorrect segmentation. Once the glass and

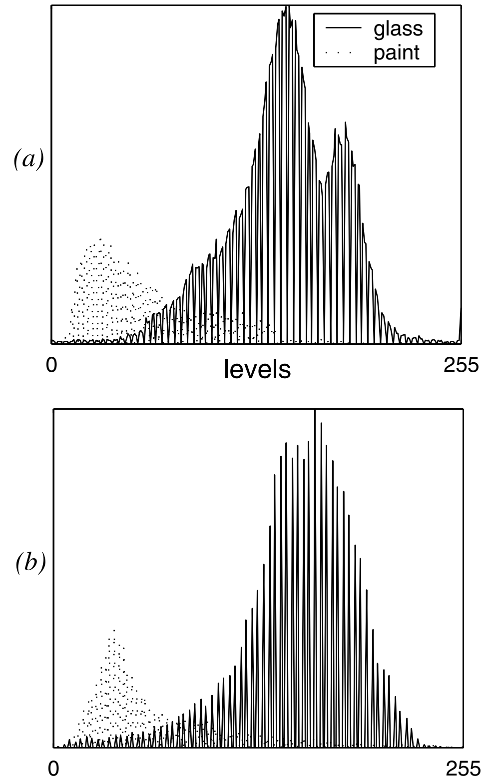


*Figure 4. Luminance histograms for the bottom (a) and top (b) sections.*

the painted lines have been separated, the average colours for the two sections (namely top section $t$ and bottom section $b$) are calculated as follows:

$$\mathbf{c}_t = \frac{1}{N_t}\sum_{i=0}^{N_t-1}\mathbf{p}_t \qquad \mathbf{c}_b = \frac{1}{N_b}\sum_{i=0}^{N_b-1}\mathbf{p}_b$$

where $\mathbf{p}_t$, $\mathbf{p}_b$ are the colour vectors of pixels respectively in the top and bottom sections, and $N_t$, $N_b$ are the number of pixels in the corresponding sections. These are subsequently equalised to the mean value $\bar{\mathbf{c}} = (\mathbf{c}_t + \mathbf{c}_b)/2$ according to:

$$\mathbf{p}_t^{(1)} = \mathbf{p}_t - \mathbf{c}_t + \bar{\mathbf{c}}$$
$$\mathbf{p}_b^{(1)} = \mathbf{p}_b - \mathbf{c}_b + \bar{\mathbf{c}}$$

Where $\mathbf{p}_t^{(1)}$, $\mathbf{p}_b^{(1)}$ are the mean-normalised pixels. Although a general equalisation is achieved, there may still be a large mismatch in the texture of the two regions.

A more sophisticated attempt to reduce such mismatch is to equalise the second statistical central moment (variance) of the two tiles:

$$\sigma_i^2 = \sum_{i=0}^{N_i-1} (\mathbf{p}_i - \mathbf{c}_i)^2 \quad i = t, b$$

The values are given in Table 1. Given that the top section yields the smaller variance, we normalise the variance of the bottom section to make it equal to the variance of the top section:

$$\mathbf{p}_b^{(2)} = \frac{\sigma_t}{\sigma_b}(\mathbf{p}_b - \mathbf{c}_b) + \bar{\mathbf{c}}$$

$$\mathbf{p}_t^{(2)} = \mathbf{p}_t^{(1)}$$

Where $\mathbf{p}_t^{(2)}$, $\mathbf{p}_b^{(2)}$ are the mean and variance normalised pixels. Note that $\mathbf{p}_t^{(2)}$ is equal to $\mathbf{p}_t^{(1)}$ since it has been shown that the top section yields the smallest variance.

| | Bottom section | | Top section | |
|---|---|---|---|---|
| | Mean | Variance | Mean | Variance |
| R | 0 | 0 | 0 | 0 |
| G | 47 | 213 | 32 | 40 |
| B | 173 | 669 | 88 | 99 |

*Table 1. Mean and variance vectors for the two sections*

In order to remove the clearly visible linear break at the junction between the two tiles, a blending technique is adopted. The pixels within a band immediately above and below the joining line $L$ are blended into a single value (graded in a direction orthogonal to the joining line) $\mathbf{p}_l(x, y) = \mathbf{p}(x, y)\big|_{x,y \in L}$, where $x$, $y$ are the spatial co-ordinates of the pixel. Successively the distance $d(x, y)$ of each pixel $\mathbf{p}^{(2)}(x, y)$ from the joining line is calculated. The new pixel value $\mathbf{p}^{(3)}$ is determined by:

$$\mathbf{p}^{(3)} = [1 - G(d)]\mathbf{p}^{(2)} + G(d)\mathbf{p}_l$$

where $\mathbf{p}_l$ is the pixel on the junction line closest to $\mathbf{p}^{(2)}$. The Gaussian function:

$$G(d) = e^{-\frac{d^2}{w^2}}$$

determines the blending according to the control parameter $w$. Therefore the closer the pixel is to the junction, the more blending is performed, as illustrated in Figure 5.

The parameter $w$ of the Gaussian function must be tuned so that unavoidable blurring artifacts are minimised as far as possible. In the image shown this parameter has been set so that the Gaussian function yields a value of 0.5 at a distance of 50 pixels from the boundary and therefore:

$$w = \sqrt{d^2 \log 2}$$

A final step is to reduce any colour vector whose norm is greater than a certain value with respect to the mean and variance:

$$\textit{if} \ \left\| \mathbf{p}_i^{(3)} - \bar{\mathbf{c}} \right\| \geq \left\| \sigma_t \right\| \ \Rightarrow \mathbf{p}_i^{(4)} = \bar{\mathbf{c}} + \alpha \cdot \frac{\left\| \sigma_t \right\| \left( \mathbf{p}_i^{(3)} - \bar{\mathbf{c}} \right)}{\left\| \mathbf{p}_i^{(3)} - \bar{\mathbf{c}} \right\|}$$

$$\alpha \in [0,1] \ i = t, b$$

The result is that any vector $\mathbf{p}^{(3)}$ outside a circle of radius $\|\sigma_t\|$ lying in the plane defined by the vectors

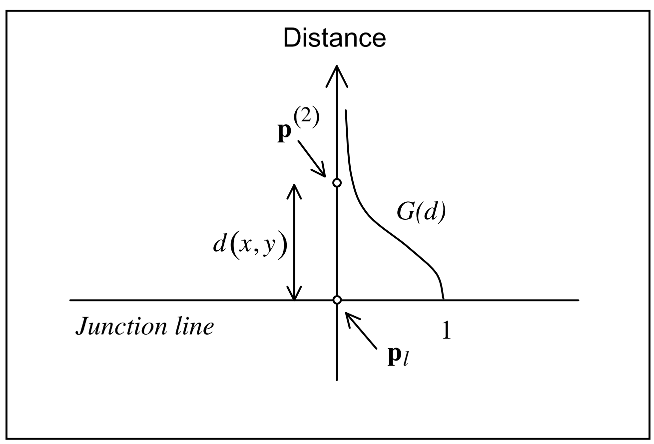


*Figure 5. Blending method*


*Figure 6. Results. (a) Original mosaic (b) Mean and variance normalisation (c) Blending (d) Removal of outliers.*

$\mathbf{p}^{(3)}$ and $\bar{\mathbf{c}}$ and centred in $\bar{\mathbf{c}}$ will be transformed into a pixel $\mathbf{p}^{(4)}$ on a circle of radius $\alpha \| \boldsymbol{\sigma}_t \|$ defined on the same plane. The rationale is that stained glass tiles have rather uniform characteristics, and most of the observed variance, in effect a texture, is due to external factors (i.e. variations in illuminance and background), and therefore must be considered as outliers of the distribution in colour space. Clearly $\alpha$ ought to be smaller than unity in order to obtain the desired effect. However a null value for $\alpha$ is not desirable as a perfectly uniform area may look too "artificial". Furthermore, hand-crafted glass typically presents variations in transmissivity which a null value of $\alpha$ would fail to simulate.

## Results

Figure 6 shows the resulting images at each stage of the algorithm. The colour mismatch between the original sections (a) has been corrected in (b) by equalising the second statistical central moment (variance) of the two tiles. In (c) the blending function has been applied across the band spanning the junction line, and finally in (d) the outlier colours (especially bright points corresponding to regions illuminated by shafts of direct sunlight) have been removed.

## References


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## Biographies

**Alfredo Giani** received his degree in Electronic Engineering from the University of Naples (Italy) in 1998 and a Ph.D. in Applied Signal Processing from the University of Southampton (United Kingdom) in 2003. Since 2002 he has worked as research assistant in the Colour and Imaging Institute, Derby (United Kingdom) and he is currently a research fellow in the Department of Information Engineering in the University of Padova (Italy). His area of expertise is in image processing and pattern recognition.

**Lindsay MacDonald** is Professor of Multimedia Imaging at the Colour & Imaging Institute of the University of Derby in the UK. He is actively involved in many research projects related to digital imaging, and is leading the European project 'Veridical Imaging of Transmissive and Reflective Artefacts' (VITRA).

He has been co-author or co-editor of seven books in the past eight years on the subjects of colour, displays, interaction and digital imaging. He has been closely involved with the IS&T/SID Color Imaging Conference (CIC) since its inception in 1993, and this year he has been made a Fellow of IS&T.