A new Infrared True-Color approach for visible-Infrared multispectral image analysis

Emanuela Grifoni[1,2], Beatrice Campanella[1], Stefano Legnaioli[1,2], Giulia Lorenzetti[1], Luciano Marras[3], Stefano Pagnotta[1], Vincenzo Palleschi[1,2*], Francesco Poggialini[1], Emanuele Salerno[4], Anna Tonazzini[4]

[1] *Applied and Laser Spectroscopy Laboratory, Institute of Chemistry of Organometallic Compounds, Research Area of CNR, Via Giuseppe Moruzzi 1, 56124 Pisa (Italy)*
[2] *National Interuniversity Consortium of Materials Science and Technology (INSTM)*
[3] *Art-Test studio di Luciano Marras, Via del Martello 14, 56121 Pisa (Italy)*
[4] *Institute of Information Science and Technologies, Research Area of CNR, Via Giuseppe Moruzzi 1, 56124 Pisa (Italy)*

***Corresponding author:**
e-mail: vincenzo.palleschi@cnr.it

Abstract

In this paper, we present a new method for the analysis of visible/Infrared multispectral sets producing chromatically faithful false-color images, which maintain a good readability of the information contained in the non-visible Infrared band. Examples of the application of this technique are given on the multispectral images acquired on the 'Pietà of Santa Croce' of Agnolo Bronzino (1569, Florence) and on the analysis and visualization of the multispectral data obtained on Etruscan mural paintings (*Tomb of the Monkey*, Siena, Italy, V century B.C.). The fidelity of the chromatic appearance of the resulting images, coupled to the effective visualization of the information contained in the Infrared band, opens interesting perspectives for the use of the method for visualization and presentation of the results of multispectral analysis in Cultural Heritage diffusion, research and diagnostics.

Keywords: Multispectral imaging, Image Fusion, Total Variation, Gradient transfer, Infrared True-Color Imaging.

1. Introduction

In the Cultural Heritage (CH) field, Imaging Spectroscopy (IS) is a well-established practice as an essential research tool both for a macroscopic qualitative analysis and for a high-quality digital documentation for a multi-temporal monitoring process of artworks [1-4]. It brings the Art Conservation studies to a more computational oriented approach, extending the deductible information on the many aspects — technical, executive and conservative — of an artifact.

Imaging Spectroscopy is based on techniques that collect different spatially co-registered images of an object. In its most typical realization, the surface of the object is irradiated with a continuous source emitting radiations in a wide portion of the electromagnetic spectrum (EM), from Ultraviolet (UV, 0.2-0.4 μm) to Infrared range (IR, 0.75-2.5 μm) while the detector is selectively adjusted to detect radiations of particular wavelengths (λ).
One of the most important advantages of this technique is that it can acquire the reflectance spectrum for each pixel of the image depending on the physical, chemical and geometric properties of the illuminated surface, i.e. the painting constituents: pigments, binding media, and varnishes.
False Color (FC) imaging is a computer-assisted technique of spectral image-fusion that improves the detecting power and extends the deductible information of a CH examination surveys. It allows a rough identification of the pigments and enhances the visualization of compositional painted changes. Restored areas, or non-original inpaints, can be better mapped in a false-color image [5].
Usually FC are trichromatic digital images obtained by swapping the three Red, Green, Blue channels (R, G, B), with an IR channel. In most of the cases, the Blue channel is removed, the Red and Green channels shift downward and the IR replaces the ex-R channel (IRRG image). In other cases, is the Red channel to be deleted and substituted with the IR channel (IRGB image) [6-7].
All these different False-Color rendering methods show the advantages above described but they also bring strong intrinsic limits: *i)* they obviously sacrifice the real color rendition of a painting, *ii)* they often produce very jumbled image not easy to be interpreted by non-specialists.
Simultaneous visualization of the preparatory drawing beneath the paint film and a chromatically faithful rendering of the painting can be an extremely useful research tool for art historians, conservators and restorers to elucidate the relationship between them, thanks to its immediacy in the information reading.
In order to satisfy this need and to provide an easy communication and data dissemination tool to let the non-specialist appreciate otherwise invisible details of a work of art, we propose a new approach, based on the Gradient Transfer (GT) method recently presented by Ma et al. [8]. This procedure has been adapted for merging the information from the IR band into the RGB image, preserving at the best the chromatic similarity with the visible image.
This result can be important to let the non-specialist appreciate otherwise invisible details of a work of art, yet leaving its overall appearance unchanged. On the other hand, even cultural heritage professionals, such as Art historians and restorers, would appreciate the possibility of studying invisible details of a painting without having recourse to a false-color approach.
The paper is organized as follows. Section 2 describes briefly the GT method and some of the mathematical machinery used to implement it. Section 3 presents a number of examples highlighting the differences between the false colors and the GT displays, and the relative advantages and disadvantages. Finally, Section 4 concludes the paper summarizing the main ideas and results.

2. Gradient Transfer Method

The Gradient Transfer method (GT) was originally proposed by Ma et al. [8] in the framework of security and military applications, for merging a thermal Infrared image with the corresponding visible image. The basic idea is to combine the information carried by the thermal image, which usually only highlights the hot spots, with the color visible image, which gives more details about the environment, to better locate hidden targets in the images.

The issue is treated as an optimization problem, where the optimum solution preserves the thermal information (i.e., minimizes the differences in intensity between each color channel of the solution

and the Infrared image), but also shows the details and the color appearance of the visible image. This second requirement corresponds to the minimization of the difference between the x and y gradients of the solution and the x and y gradients of the visible image.
How such optimization problem can be solved through a Total Variation regularization method is shown below. Before going into the mathematical details, however, it is worth noting that the technique, in its original formulation, seems to be of relatively scarce utility in painting analysis, where the Infrared image might carry information about *underdrawing* and *pentimenti*, whose details one would like to preserve in the optimum solution. The only possible exception seems to be the analysis of *Visible-Induced Luminescence* (VIL) images [9], where the IR image typically consists of a few bright zones, corresponding to the highly fluorescent materials, on a dark background.
In our approach, instead, we try to get a solution preserving, as much as possible, the original observed colors and the gradients of the Infrared channel. To this end, we build a convex, non-smooth objective function whose minimization yields our optimal solution.
Let A be the observed color image, m pixels wide and n pixels tall, composed by its red, green and blue channels A_c, $c=\{r,g,b\}$. Then, let B be the observed Infrared channel, and $X=(X_r,X_g,X_b)$ our solution image. All the channel images are represented as $m\times n$ matrices with pixel intensities ranging from 0 to 1.
The first requirement for our solution X is that each of its channels must be similar to the corresponding channel of the observed image A. As a measure of deviation from this requirement, we use the squared Frobenius norm of the difference between each pair of channels:

$$\|X_c - A_c\|_F^2 = \sum_{i=1}^{m}\sum_{j=1}^{n}[X_c(i,j) - A_c(i,j)]^2 , \quad c\, \epsilon\, \{r,g,b\} \tag{1}$$

where (i,j) is the pixel index.

At the same time, for preserving the details from B in the solution, we also require that the sum of the absolute differences between the gradients of each channel of image X and the gradients of image B is as small as possible. Our measure of deviation is now the Total Variation norm [10] of the matrices $(X_c–B)$:

$$|X_c - B|_{TV} = \sum_{i=1}^{m}\sum_{j=1}^{n}|\nabla X_c(i,j) - \nabla B(i,j)| \quad , \quad c\, \epsilon\, \{r,g,b\} \tag{2}$$

In order to minimize (1) and (2) simultaneously, the problem to be solved is the following:

$$\widehat{X_c} = \underset{X_c}{arg\ min}\, \{\|X_c - A_c\|_F^2 + \lambda\, |X_c - B|_{TV}\, \} \ , \quad c\, \epsilon\, \{r,g,b\} \tag{3}$$

where λ is a positive regularization parameter that weights the relative strength of the two constraints. Both intuitively and mathematically, λ makes the solution X_c more similar to image A_c, for $\lambda \to 0$, or to B, for $\lambda \to \infty$. The choice of this parameter, then, should result from a compromise between the fidelity to the original RGB and the visibility of the IR gradients.

Letting $Y_c=X_c–B$ and $D_c=A_c–B$, the three optimization problems in (3) can equivalently be put in the form:

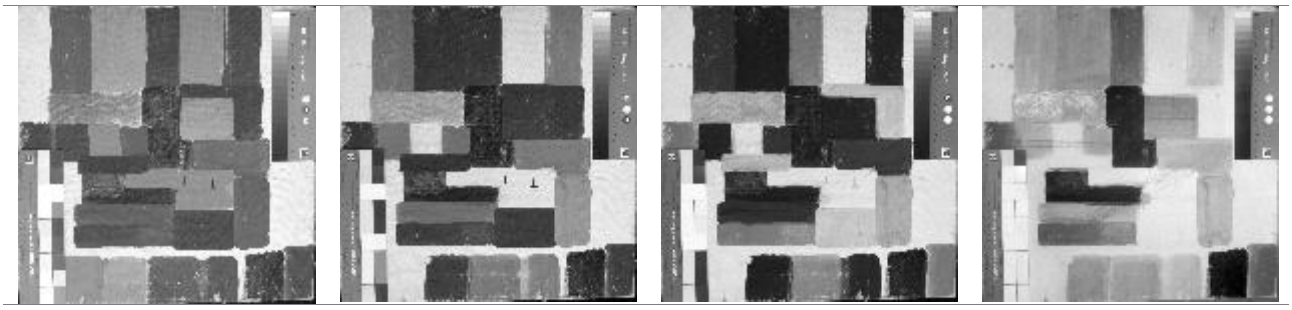
$$\widehat{Y_c} = \underset{Y_c}{arg\ min}\, \{\|Y_c - D_c\|_F^2 + \lambda\, |Y_c|_{TV}\, \} \ , \quad c\, \epsilon\, \{r,g,b\}$$

$$\widehat{X_c} = \widehat{Y}_c + B \tag{4}$$

At each *c*, the corresponding optimization problem in eq. (4) has the well-known form of the optimization problem in Total Variation regularization. This technique is widely used in inverse, ill-posed imaging problems, such as denoising [10-11].
Since the function to be minimized is convex, a number of convex optimization algorithms exists for determining its optimum solution. In this paper, we use the Regularized Linear Regression solver included in the Matlab® UNLockBoX Convex Optimization Toolbox [12]. This solver uses the forward-backward splitting algorithm [13], specifically designed to minimize convex functions of the same form of the one in eq. (4), where the second term is not differentiable. The method implemented exploits the proximal operator [14] of the non-differentiable term to find iteratively the variable to be estimated. At each iteration, the update chosen finds, by an inner iterative cycle, the smallest value of the non-differentiable term in a neighborhood of the ordinary gradient-descent update of the differentiable term. Under mild conditions, this procedure is proved to converge to the minimizer of the original Total Variation problem. The solutions to the three independent problems in eq. (4) can then be composed to give the RGB image *X*.

3. Examples

As a first example of the application of the above described method is the analysis of a set of multispectral images in which the Infrared image contains details worth to be evidenced in a False-Color image, as the ones shown in figure 1. The images were acquired using a Multispectral Camera (Moravian G2-8300, 8 Mpixel-16 bit greyscale camera equipped with 9 filters, bandpass ± 25 nm).



Blue (450 nm) Green (550 nm) Red (650 nm) IR (1050 nm)

Fig. 1 – Visible and Infrared images of a test canvas.

The RGB color image of a test canvas, used in our laboratory for didactical purposes, is shown in figure 2, compared to the IR image. The visible image was obtained by combining the Blue, Green and Red channels in figure 1.

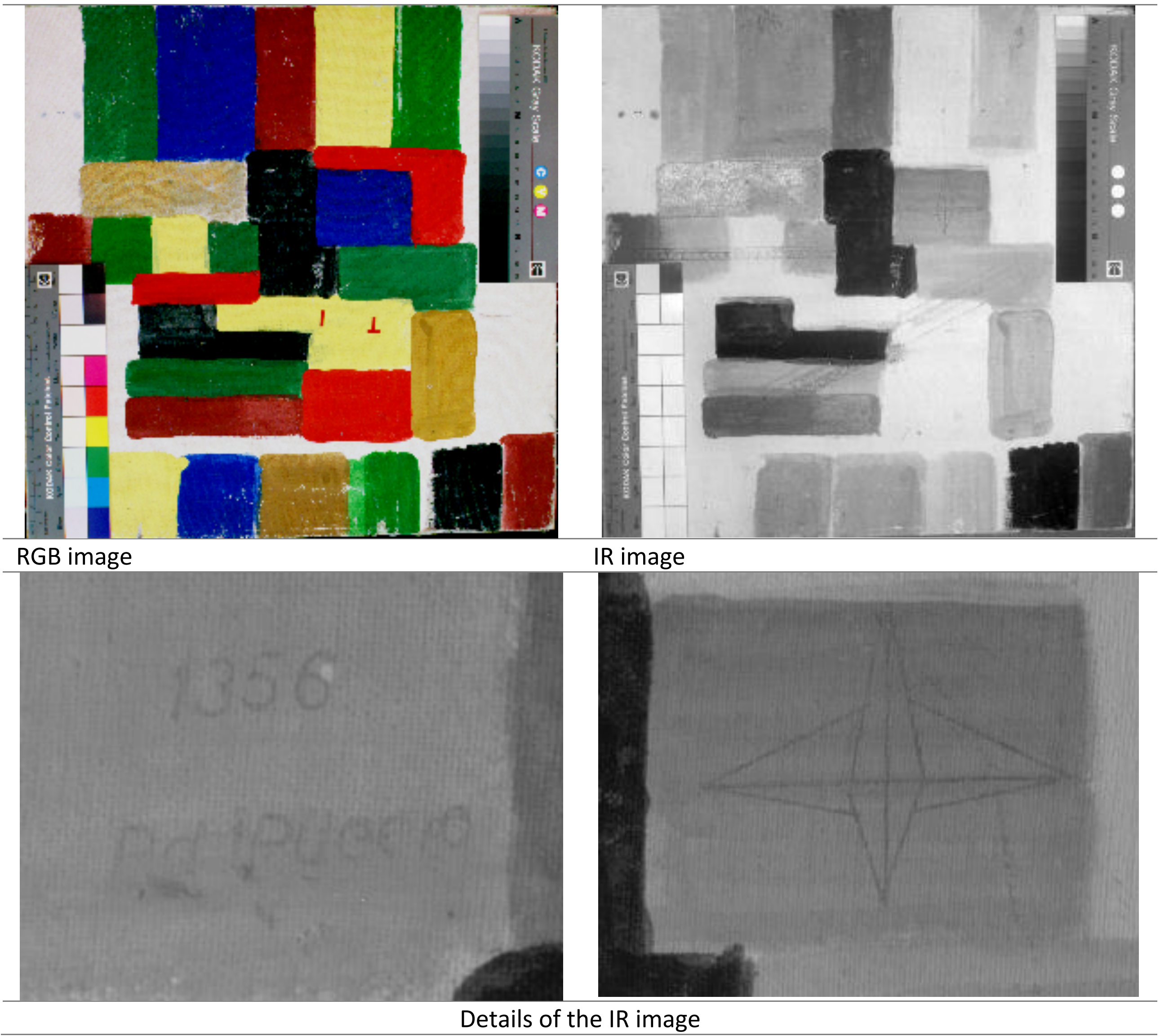


Fig. 2 – RGB and Infrared image of a test canvas.

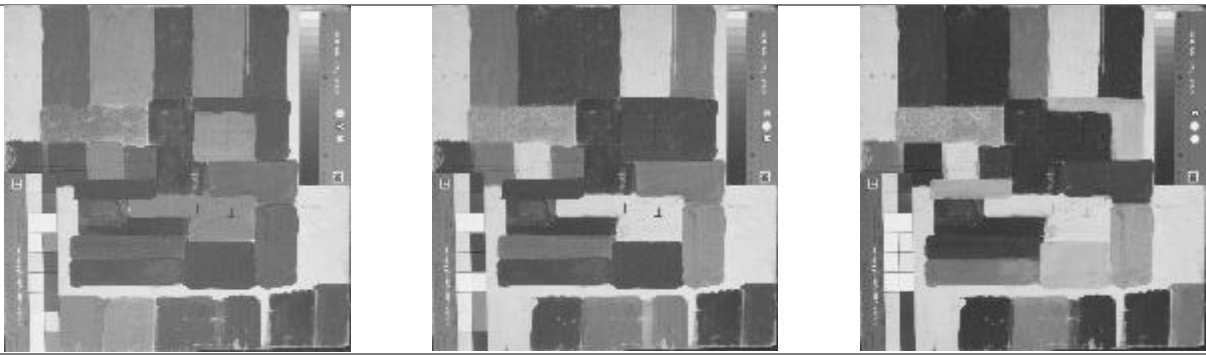
One of the characteristics of our test canvas is the presence of underdrawings that are not visible at naked eye (under the two blue patches on the top of the canvas, see figure 2).
The usual approach to evidence these features would be the application of the IRRG or IRGB false-color method (figure 3).

IRRG false-color image IRGB false-color image

Fig. 3 – IRRG and IRGB false-color images of a test canvas.

Although both the two false-color approaches are able to evidence the previously invisible underdrawings, the colors are not realistic (and, in fact, the False-Colors obtained using the IRRG method are often used as a tool for a rough identification of the pigments used in the painting). The method that we propose in this paper aims to obtain the same (or better) visibility of the underdrawing or of the other details evidenced in the IR image, maintaining the visual appearance of the RGB image.

For doing that, we should just identify the matrix ***A*** in eq. (3) with one of the components of the RGB image, while ***B*** will be the Infrared image. The results of the three optimizations (λ = 0.05) for the three components of the visible image are shown in figure 4.



Blue + IR Green + IR Red + IR

Figure 4 – Mixed components after optimization of eq. (3).

The details of the underdrawing are visible in all the three components. The composition of the mixed images in a false-color image is shown in figure 5.

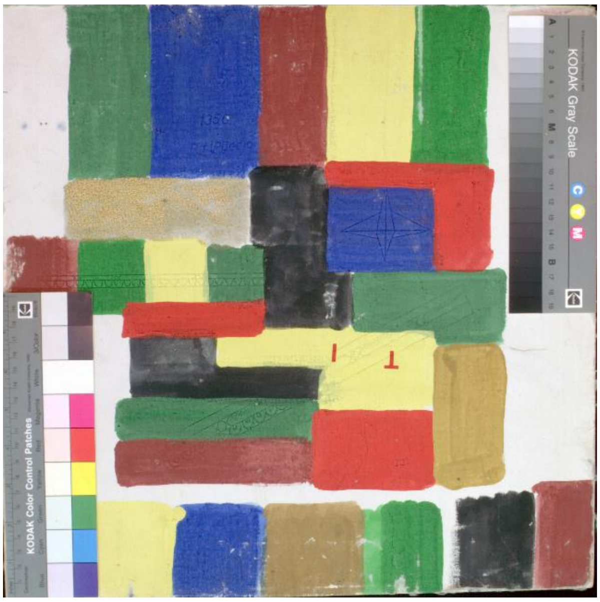
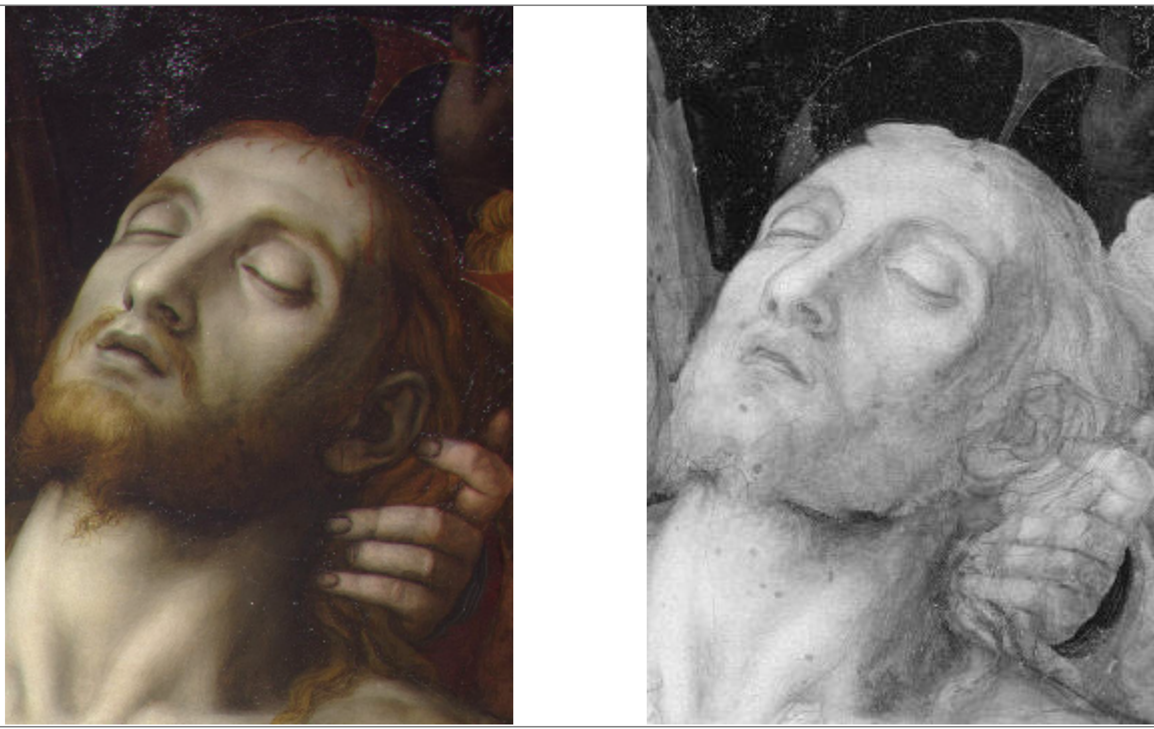


Figure 5 –Realistic false-color imgage obtained using the Gradient Transfer method.

A comparison of figure 5 with the false-color images in figure 3 evidences that, while the underdrawings are clearly visible (from the Gradient Transfer of the IR image details), the visual appearance of the canvas and the colors are almost perfectly preserved (see figure 2). We can thus call this particular application of the Gradient Transfer method ‘Infrared true-color’ (IR-TC) imaging. Another example of the application of Gradient Transfer for obtaining a realistic False-Color image involves the elaboration of a detail of the panel painting *Pietà*, dated 1569, by Agnolo Bronzino, conserved in Santa Croce, Florence. The multispectral images were obtained by one of us (Luciano Marras) using a motorized flat scanner (spatial resolution: 250 μm, acquisition time: 90 min/m^2) [15]. The RGB and IR images are shown in figure 6.



RGB Image	IR Image (1000/1700 nm)

Figure 6 – RGB and IR Image of the ‘Pietà’ (detail).

The Bronzino painting is characterized by many *pentimenti*, which can be studied using the classical false-color approaches (figure 7)

IRRG False-color image	IRGB False-color image

Figure 7 – IRRG and IRGB false-color images of the ‘Pietà’.

The false-color images evidence clearly the *pentimenti*. However, the chromatic rendering of the images are very different from the original.

The IR-TC image shown in figure 8 was obtained through the optimization of eq. (3) with $\lambda = 0.005$.

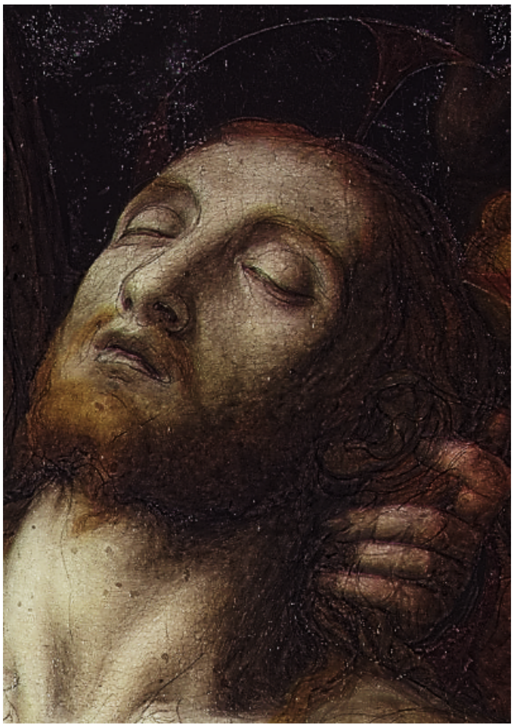


Figure 8 – IR-TC reconstruction of the 'Pietà'.

The application of this method is not limited to canvas or wood painting. In figure 9 we show the RGB image and the IR image of an Etruscan wall painting (*Tomb of the Monkey*, Chiusi, Italy) [16-17].

RGB Image | Infrared image (1050 nm)

Figure 9 – RGB and Infrared Image of an Etruscan wall painting.

The realistic false-color image is shown in figure 10, compared to the conventional IRRG and IRGB false color images.

Realistic false-color | IRRG | IRGB

Figure 10 – IR-TC image, compared with IRRG and IRGB false-color.

4. Related works

Total Variation (TV) regularization is a technique widely used in inverse, ill-posed imaging problems, for its ability to perform local smoothness, i.e., to promote flat regions in the image to be reconstructed while preserving the edges [18]. Compared to other edge-preserving regularizers, total variation applied to the inversion of linear data models has the further advantage of resulting in a convex optimization problem. The unique solution can thus be computed by solving the associated Euler-Lagrange equation, or by using one of the several algorithms for convex minimization.
Total variation was originally introduced for image denoising [19], and then applied to several other imaging problems [10], including deblurring [11], blind deconvolution [20], inpainting [21], and color demosaicing [22].
An interesting approach for merging hyperspectral and visible imaging, preserving the fidelity of the RGB image colour and the details of the IR image, has been proposed by Kim et al. [23] for the analysis of old documents. Another recent proposal for enhancement of ancient documents based on the merging of RGB and IR images has been presented by Gargano et al. [24].

5. Conclusion

We have presented a new method for the realization of realistic false-color images, based on the Gradient Transfer algorithm recently proposed by Ma et al. [8] for the treatment of thermal Infrared images. The Gradient Transfer idea, suitably modified for the application to Cultural Heritage multispectral analysis, allows the merging of visible and Infrared information that guarantees a good chromatic fidelity of the result with the original RGB image while preserving the readability of the details contained in the Infrared image. We believe that such Infrared True-Color images can be very useful for restorers and Art historians as a support of their activity, but also, in museums and exhibitions, for augmented reality applications in which the otherwise invisible Infrared details or underdrawings can be made visible to the public without changing the chromatic appearance of the original.

References

[1] Marengo, E., Manfredi, M., Zerbinati, O., Robotti, E., Mazzucco, E., Gosetti, F., Bearman, G., France, F., Shor, P., Development of a technique based on multi-spectral imaging for monitoring the conservation of cultural heritage objects (2011) Analytica Chimica Acta, 706 (2), 229-237.

[2] Cucci, C., Delaney, J.K., Picollo, M., Reflectance Hyperspectral Imaging for Investigation of Works of Art: Old Master Paintings and Illuminated Manuscripts (2016) Accounts of Chemical Research, 49 (10), 2070-2079.

[3] Delaney, J.K., Trumpy, G., Didier, M., Ricciardi, P., Dooley, K.A., A high sensitivity, low noise and high spatial resolution multi-band Infrared reflectography camera for the study of paintings and works on paper (2017) Heritage Science, 5 (1), art. no. 32.

[4] Polak, A., Kelman, T., Murray, P., Marshall, S., Stothard, D.J.M., Eastaugh, N., Eastaugh, F., Hyperspectral imaging combined with data classification techniques as an aid for artwork authentication (2017) Journal of Cultural Heritage, 26, 1-11.

[5] Cucci C., Delaney, J. K., Picollo M., Reflectance Hyperspectral Imaging for Investigation of Works of Art: Old Master Paintings and Illuminated Manuscripts (2016) Acc. Chem. Res. 2016, 49, 2070−2079.

[6] Aldrovandi, A., Buzzegoli, E., Keller, A., Kunzelman, D., Indagini su superfici dipinte mediante immagini UV riflesse in falso colore (2004) OPD Restauro 16, 83-87, 197-199.

[7] Pelagotti, A., Pezzati, L., Piva, A., & Del Mastio, A., Multispectral UV Fluorescence Analysis of painted surfaces (2006) 14th European Signal Processing Conference (EUSIPCO 2006). Florence, Italy.

[8] Ma, J., Chen, C., Li, C., Huang, J., Infrared and visible image fusion via gradient transfer and Total Variation minimization (2016) Information Fusion, 31, 100-109.

[9] Verri, G., The application of visible-induced luminescence imaging to the examination of museum objects (2009) Proceedings of SPIE - The International Society for Optical Engineering, 7391, art. no. 739105.

[10] Chambolle, A., An Algorithm for Total Variation Minimization and Applications (2004) Journal of Mathematical Imaging and Vision, 20 (1-2), 89-97.

[11] Beck, A., Teboulle, M., Fast gradient-based algorithms for constrained Total Variation image denoising and deblurring problems (2009) IEEE Transactions on Image Processing, 18 (11), 2419-2434.

[12] Perraudin, N., Kalofolias, V., Shuman, D., Vandergheynst, P., UNLocBoX: A MATLAB convex optimization toolbox for proximal-splitting methods, arXiv:1402.0779.

[13] Combettes, P.L., Pesquet, J.-C., A Douglas-Rachford splitting approach to nonsmooth convex variational signal recovery (2007) IEEE Journal on Selected Topics in Signal Processing, 1 (4), 564-574.

[14] Parikh, N., Boyd, S., Proximal algorithms, Foundation and Trends® in Optimization, Vol. 1, No. 3 (2013), pp. 123-231.

[15] Marras, L., Grifoni, E., La pietà di Agnolo Bronzino. Indagini diagnostiche, Art-Test Editore, 2014, ISBN-13: 9788890932014 (in Italian).

[16] Legnaioli, S., Lorenzetti, G., Cavalcanti, G.H., Grifoni, E., Marras, L., Tonazzini, A., Salerno, E., Pallecchi, P., Giachi, G., Palleschi, V., Recovery of archaeological wall paintings using novel multispectral imaging approaches (2013) Heritage Science, 1 (1), art. no. 33.

[17] Salerno, E., Tonazzini, A., Grifoni, E., Lorenzetti, G., Legnaioli, S., Lezzerini, M., Palleschi, V., Analysis of Multispectral Images in Cultural Heritage and Archaeology (2014) Journal of Applied and Laser Spectroscopy JALS, 1, 22-27.

[18] Strong, D.; Chan, T., Edge-preserving and scale-dependent properties of total variation regularization (2003) Inverse Problems, 19: S165–S187.

[19] Rudin, L. I.; Osher, S.; Fatemi, E., Nonlinear total variation based noise removal algorithms (1992) Physica D. 60: 259–268.

[20] Chan, T.F., Wong, C.-K., Total Variation Blind Deconvolution (1998) IEEE Transactions on Image Processing, 7 (3), 370-375.

[21] Chan, T.F., Shen, J., Zhou, H.-M., Total Variation Wavelet Inpainting (2006) Journal of Mathematical Imaging and Vision, 25, 107-125.

[22] Condat, L., Mosaddegh, S., Joint demosaicing and denoising by total variation minimization (2012) in Proc. IEEE International Conference on Image Processing (ICIP), 2012, pp. 2781-2784.

[23] Kim, S.J., Deng, F., Brown, M.S., Visual enhancement of old documents with hyperspectral imaging (2011) Pattern Recognition, 44 (7), pp. 1461-1469

[24] Gargano, M., Bertani, D., Greco, M., Cupitt, J., Gadia, D., Rizzi, A., A perceptual approach to the fusion of visible and NIR images in the examination of ancient documents (2015) Journal of Cultural Heritage, 16 (4), pp. 518-525.