

1 A new Infrared True-Color approach for visible-Infrared 2 multispectral image analysis

3
4 Emanuela Grifoni^{1,2}, Beatrice Campanella¹, Stefano Legnaioli^{1,2}, Giulia Lorenzetti¹,
5 Luciano Marras³, Stefano Pagnotta¹, Vincenzo Palleschi^{1,2*}, Francesco Poggialini¹,
6 Emanuele Salerno⁴, Anna Tonazzini⁴

7
8 ¹*Applied and Laser Spectroscopy Laboratory, Institute of Chemistry of Organometallic Compounds, Research
9 Area of CNR, Via Giuseppe Moruzzi 1, 56124 Pisa (Italy)*

10 ²*National Interuniversity Consortium of Materials Science and Technology (INSTM)*

11 ³*Art-Test studio di Luciano Marras, Via del Martello 14, 56121 Pisa (Italy)*

12 ⁴*Institute of Information Science and Technologies, Research Area of CNR, Via Giuseppe Moruzzi 1, 56124
13 Pisa (Italy)*

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15

16 ***Corresponding author:**

17 e-mail: vincenzo.palleschi@cnr.it

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20 **Abstract**

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

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

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36 **1. Introduction**

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

43 Imaging Spectroscopy is based on techniques that collect different spatially co-registered images of
44 an object. In its most typical realization, the surface of the object is irradiated with a continuous
45 source emitting radiations in a wide portion of the electromagnetic spectrum (EM), from Ultraviolet
46 (UV, 0.2-0.4 μm) to Infrared range (IR, 0.75-2.5 μm) while the detector is selectively adjusted to
47 detect radiations of particular wavelengths (λ).

48 One of the most important advantages of this technique is that it can acquire the reflectance
49 spectrum for each pixel of the image depending on the physical, chemical and geometric properties
50 of the illuminated surface, i.e. the painting constituents: pigments, binding media, and varnishes.

51 False Color (FC) imaging is a computer-assisted technique of spectral image-fusion that improves
52 the detecting power and extends the deductible information of a CH examination surveys. It allows
53 a rough identification of the pigments and enhances the visualization of compositional painted
54 changes. Restored areas, or non-original inpaints, can be better mapped in a false-color image [5].
55 Usually FC are trichromatic digital images obtained by swapping the three Red, Green, Blue channels
56 (R, G, B), with an IR channel. In most of the cases, the Blue channel is removed, the Red and Green
57 channels shift downward and the IR replaces the ex-R channel (IRRG image). In other cases, is the
58 Red channel to be deleted and substituted with the IR channel (IRGB image) [6-7].

59 All these different False-Color rendering methods show the advantages above described but they
60 also bring strong intrinsic limits: *i)* they obviously sacrifice the real color rendition of a painting, *ii)*
61 they often produce very jumbled image not easy to be interpreted by non-specialists.

62 Simultaneous visualization of the preparatory drawing beneath the paint film and a chromatically
63 faithful rendering of the painting can be an extremely useful research tool for art historians,
64 conservators and restorers to elucidate the relationship between them, thanks to its immediacy in
65 the information reading.

66 In order to satisfy this need and to provide an easy communication and data dissemination tool to
67 let the non-specialist appreciate otherwise invisible details of a work of art, we propose a new
68 approach, based on the Gradient Transfer (GT) method recently presented by Ma et al. [8]. This
69 procedure has been adapted for merging the information from the IR band into the RGB image,
70 preserving at the best the chromatic similarity with the visible image.

71 This result can be important to let the non-specialist appreciate otherwise invisible details of a work
72 of art, yet leaving its overall appearance unchanged. On the other hand, even cultural heritage
73 professionals, such as Art historians and restorers, would appreciate the possibility of studying
74 invisible details of a painting without having recourse to a false-color approach.

75 The paper is organized as follows. Section 2 describes briefly the GT method and some of the
76 mathematical machinery used to implement it. Section 3 presents a number of examples
77 highlighting the differences between the false colors and the GT displays, and the relative
78 advantages and disadvantages. Finally, Section 4 concludes the paper summarizing the main ideas
79 and results.

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81 **2. Gradient Transfer Method**

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

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

91 and the Infrared image), but also shows the details and the color appearance of the visible image.
 92 This second requirement corresponds to the minimization of the difference between the x and y
 93 gradients of the solution and the x and y gradients of the visible image.
 94 How such optimization problem can be solved through a Total Variation regularization method is
 95 shown below. Before going into the mathematical details, however, it is worth noting that the
 96 technique, in its original formulation, seems to be of relatively scarce utility in painting analysis,
 97 where the Infrared image might carry information about *underdrawing* and *pentimenti*, whose
 98 details one would like to preserve in the optimum solution. The only possible exception seems to
 99 be the analysis of *Visible-Induced Luminescence* (VIL) images [9], where the IR image typically
 100 consists of a few bright zones, corresponding to the highly fluorescent materials, on a dark
 101 background.

102 In our approach, instead, we try to get a solution preserving, as much as possible, the original
 103 observed colors and the gradients of the Infrared channel. To this end, we build a convex, non-
 104 smooth objective function whose minimization yields our optimal solution.

105 **Let A be the observed color image, m pixels wide and n pixels tall, composed by its red, green and**
 106 **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
 107 solution image. All the channel images are represented as $m \times n$ matrices with pixel intensities
 108 ranging from 0 to 1.

109 The first requirement for our solution X is that each of its channels must be similar to the
 110 corresponding channel of the observed image A . As a measure of deviation from this requirement,
 111 we use the squared Frobenius norm of the difference between each pair of channels:

$$112 \quad \|X_c - A_c\|_F^2 = \sum_{i=1}^m \sum_{j=1}^n [X_c(i, j) - A_c(i, j)]^2, \quad c \in \{r, g, b\} \quad (1)$$

114 where (i, j) is the pixel index.

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

$$122 \quad |X_c - B|_{TV} = \sum_{i=1}^m \sum_{j=1}^n |\nabla X_c(i, j) - \nabla B(i, j)|, \quad c \in \{r, g, b\} \quad (2)$$

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

$$126 \quad \widehat{X}_c = \arg \min_{X_c} \{ \|X_c - A_c\|_F^2 + \lambda |X_c - B|_{TV} \}, \quad c \in \{r, g, b\} \quad (3)$$

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

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

$$136 \quad \widehat{Y}_c = \arg \min_{Y_c} \{ \|Y_c - D_c\|_F^2 + \lambda |Y_c|_{TV} \}, \quad c \in \{r, g, b\}$$

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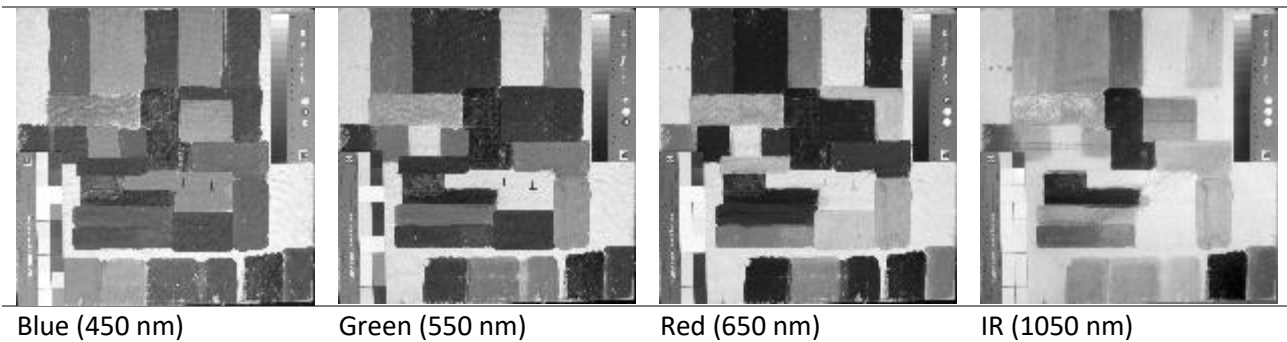
$$\widehat{X}_c = \widehat{Y}_c + B$$

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

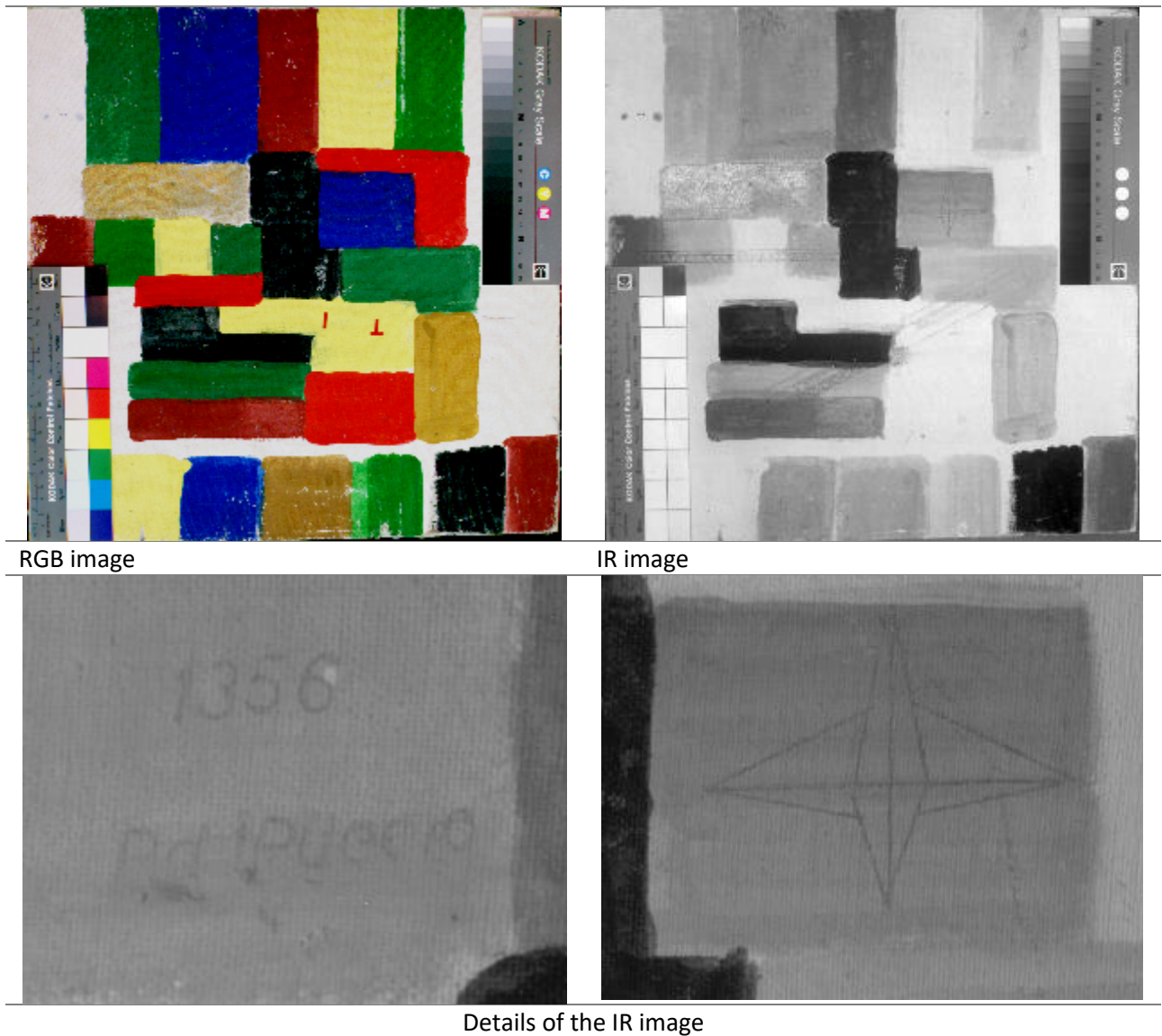
As a first example of the application of the above described method is the analysis of a set of multispectral images in which the Infrared image contains details worth to be evidenced in a False-Color image, as the ones shown in figure 1. **The images were acquired using a Multispectral Camera (Moravian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



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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.

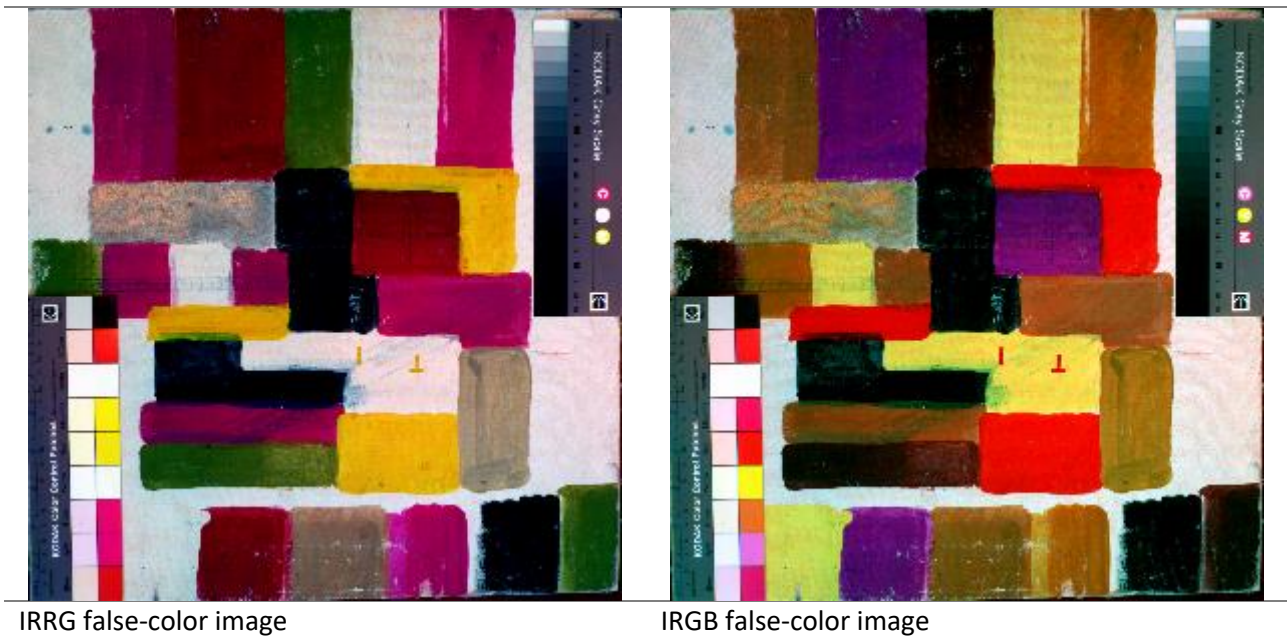


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Fig. 2 – RGB and Infrared image of a test canvas.

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).

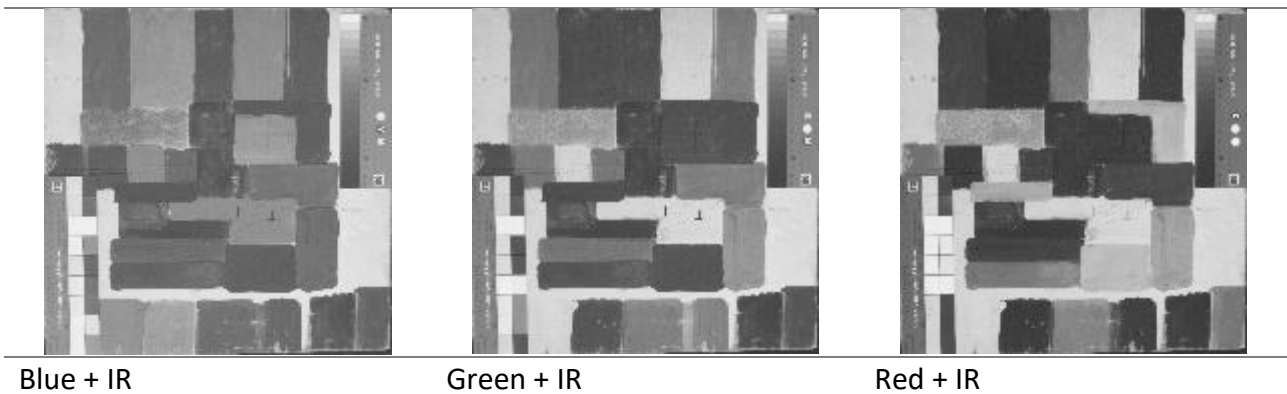
The usual approach to evidence these features would be the application of the IRRG or IRGB false-color method (figure 3).



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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 \mathbf{A} in eq. (3) with one of the components of the RGB image, while \mathbf{B} will be the Infrared image. The results of the three optimizations ($\lambda = 0.05$) for the three components of the visible image are shown in figure 4.



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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 image obtained using the Gradient Transfer method.

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200 A comparison of figure 5 with the false-color images in figure 3 evidences that, while the
201 underdrawings are clearly visible (from the Gradient Transfer of the IR image details), the visual
202 appearance of the canvas and the colors are almost perfectly preserved (see figure 2). We can thus
203 call this particular application of the Gradient Transfer method ‘Infrared true-color’ (IR-TC) imaging.
204 Another example of the application of Gradient Transfer for obtaining a realistic False-Color image
205 involves the elaboration of a detail of the panel painting *Pietà*, dated 1569, by Agnolo Bronzino,
206 conserved in Santa Croce, Florence. **The multispectral images were obtained by one of us (Luciano
207 Marras) using a motorized flat scanner (spatial resolution: 250 μm , acquisition time: 90 min/m²)
208 [15]. The RGB and IR images are shown in figure 6.**
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RGB Image

IR Image (1000/1700 nm)

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212 Figure 6 – RGB and IR Image of the 'Pietà' (detail).

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214 The Bronzino painting is characterized by many *pentimenti*, which can be studied using the classical

215 false-color approaches (figure 7)

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IRRG False-color image

IRGB False-color image

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218 Figure 7 – IRRG and IRGB false-color images of the 'Pietà'.

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

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222 The IR-TC image shown in figure 8 was obtained through the optimization of eq. (3) with $\lambda = 0.005$.
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226 Figure 8 – IR-TC reconstruction of the ‘Pietà’.

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228 The application of this method is not limited to canvas or wood painting. In figure 9 we show the
229 RGB image and the IR image of an Etruscan wall painting (*Tomb of the Monkey*, Chiusi, Italy) [16-
230 17].
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RGB Image

Infrared image (1050 nm)

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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

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

243 **4. Related works**

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245 Total Variation (TV) regularization is a technique widely used in inverse, ill-posed imaging problems,
246 for its ability to perform local smoothness, i.e., to promote flat regions in the image to be
247 reconstructed while preserving the edges [18]. Compared to other edge-preserving regularizers,
248 total variation applied to the inversion of linear data models has the further advantage of resulting
249 in a convex optimization problem. The unique solution can thus be computed by solving the
250 associated Euler-Lagrange equation, or by using one of the several algorithms for convex
251 minimization.

252 Total variation was originally introduced for image denoising [19], and then applied to several other
253 imaging problems [10], including deblurring [11], blind deconvolution [20], inpainting [21], and color
254 demosaicing [22].

255 An interesting approach for merging hyperspectral and visible imaging, preserving the fidelity of the
256 RGB image colour and the details of the IR image, has been proposed by Kim et al. [23] for the
257 analysis of old documents. Another recent proposal for enhancement of ancient documents based
258 on the merging of RGB and IR images has been presented by Gargano et al. [24].

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261 **5. Conclusion**

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

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