NOVEL DATA REGISTRATION TECHNIQUES FOR ART DIAGNOSTICS AND 3D HERITAGE VISUALIZATION

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Abstract: In Cultural Heritage applications, as often in the medical field, diagnoses have to be accomplished by comparing data obtained with different techniques and sensors. However, the acquired data are often misaligned and in order to exactly superimpose them, they need to be correctly registered among each other. In this contribution we present an automatic feature-based registration technique to align image data. Moreover, since 2D images acquired with various devices are generally of easier interpretation when mapped onto a 3D model or produce nicer and photo-realistic visualization results, we propose an automated method to map 2D images onto 3D surfaces. Results are presented and discussed.

1. Introduction

Similarly to what happens in the medical field, also for art diagnostics and visual Cultural Heritage it is often needed to compare and integrate different sets of information, coming from different sources and stored in different datasets. In order to successfully integrate these data, features corresponding to the same areas need to be registered. Registration is therefore the determination of a geometrical transformation that aligns features in one dataset with the corresponding features in another dataset. Data registration is necessary as the information might come from:

- Different imaging sensors *(multimodal data)*: data related to the same object or scene are acquired by different sensors e.g. working in different parts of the light spectrum. These data need afterwards to be aligned and overlapped for information fusion, multispectral analysis or other diagnostic applications.
- Different viewpoints (*multiview data*): data of the same object or scene are acquired from different standpoints for 3D reconstruction purposes or to generate high-resolution views or panoramas.
- Different acquisition times (*multitemporal data*): data of the same object or scene are acquired at different times e.g. to evaluate changes or movements.

Data registration is often performed manually, iteratively setting the parameters of the geometrical transformation or interactively seeking the corresponding features. However, these approaches are time consuming and can give subjective results. Registration can be performed between 2D-2D data (e.g. images), 2D-3D data (e.g. an image mapped onto a 3D model) or 3D-3D (e.g. range maps). Due to the diversity of data that can be registered, it is difficult to define a standard approach suitable in all the possible applications. Nevertheless, most of the techniques are based on the following steps:

- Primitives detection: interest points, salient regions or edges are extracted (preferably automatically) and often associated to a feature vector (descriptors) for the successive processing (matching).
- Matching: correspondences between the detected features are sought and established, generally pair-wise, using similarity measures and correlation methods.
- Transformation model estimation: the parameters of the mathematical model used for the alignment are computed using the obtained correspondences or the entire data.
- Data alignment and transformation: using the computed transformation parameters, the data are registered, mapped or aligned.

In this contribution, beside a quick review of the state of the art registration methods for 2D and 3D data, we present two methods for the automated alignment between (i) multimodal images of paintings acquired with multi-spectral systems (Section 2.3) and (ii) between images and 3D models for texture mapping applications (Section 3.1). The two developed automated registration techniques are based on feature- and intensity-based approaches. They have been tested on multi-spectral data, including IR and UV fluorescence images of paintings, as well as on 3D data coming from photogrammetric or range-based 3D modeling.

2. 2D-2D data registration

2D data are primarily images or maps which need to be registered for mosaicking, 3D geometry extraction, art diagnostic, change detection, etc. The 2D data need to be registered as they might be taken at different times (e.g. historical pictures versus current pictures), from different points of view or by means of different sensors acquiring the images in different spectral bands (e.g. IR-reflectograms, X-radiographies). In these cases, the acquired images will capture different and often complementary contents that thanks to the registration can allow an integrated visualization of the scene. As mentioned earlier, some primitives (i.e. features like points, lines or regions) need to be firstly detected and then matched to establish the correspondences required to compute the transformation parameters needed for the data alignment. The transformation model is generally obtained using an affine transformation (6 parameters) even if a projective (8 parameters) or more complex models can be used. An overview of image registration techniques is presented in [1]. Other authors [2, 3] classified the different registration algorithms according to six fundamental properties: the scene representation, photo-consistency measure, visibility model, shape prior, reconstruction algorithm, and initialization requirements. On the other hand, following [4] we consider the two main classes of matching primitives, i.e. image intensity patterns (windows composed of grey values around a point of interest) and features (edges and regions), which arise to registration methods generally classified as area-based and feature-based procedures.

2.1. Area-based registration procedure

Area-based methods are mainly based on squared, rectangular or circular windows around an interest point [5, 7, 8, 9] or even on the entire images. If small windows are used, a match is established using cross-correlation methods [10] or least squares matching [11] while Fourier [12, 13, 14] and the Maximization of the Mutual Information (MMI) [15, 16, 17, 18] methods are generally applied to the entire images. The MMI method is an interesting and powerful registration approach originating from the information theory and particularly suitable for registration of images achieved in different modalities. The MMI method has been recently used for medical imaging [19] and Cultural Heritage applications (multispectral analysis of pigments) [20, 21] proving to be highly effective, due to its flexibility and capability in registering images with very few features in common (multimodal images). The MMI seeks a measure of the statistical dependency between the two data sets through a criterion which states that two images are correctly aligned when the Mutual Information assumes its maximum value. Given two images *X* and *Y*, related by a geometric transformation T_α such that the pixel *p* of *X* (whose intensity is *x*) corresponds to the pixel $T_\alpha(p)$ of *Y* (whose intensity is *y*), the MI of the two images is given by:

$$MI(X;Y) = \sum_{x,y} p_{XY}(x,y) \cdot \log_2 \frac{p_{XY}(x,y)}{p_X(x) \cdot p_Y(y)} \tag{1}$$

where $p_{XY}(x,y)$ is the joint probability distribution of the two images, and $p_X(x)$ and $p_Y(y)$ are their marginal probability distribution. Marginal and joint probability distributions can be estimated with the normalization of the *joint histogram* (say $h_\alpha(x,y)$) of the two images, which is obtained by binning the intensity value pairs $x = X(p)$ and $y = Y(T_\alpha(p))$, for all the pixels and depending on each accounted transform [16]:

$$p_{XY,\alpha}(x,y) = \frac{h_\alpha(x,y)}{\sum_{x,y} h_\alpha(x,y)} \quad p_{X,\alpha}(x) = \sum_y p_{XY,\alpha}(x,y) \quad p_{Y,\alpha}(y) = \sum_x p_{XY,\alpha}(x,y) \tag{2}$$

MMI is a very general and powerful criterion, since no assumptions are made over the nature of this dependence and no constraints are posed on the image contents, thus enforcing the MMI criterion to be particularly effective when a low amount of information is shared between the two images. But the MMI method is generally computationally quite slow, in particular when using large images, such as generally those of artworks. In order to speed it up, the method needs indeed an initial guess of the unknown transformation parameters, which is generally provided together with a search intervals and incremental steps.

2.2. Feature-based registration procedure

Feature-based registration methods use features like regions [22, 23, 24, 9] or edges [25]. The features are firstly identified in the images, then described using some particular invariant descriptors [26, 27, 28] and finally matched using spatial relations [29, 30], relaxation methods [31, 32], wavelets [33, 34] or descriptor similarities [35]. Feature-based registration methods are used when the local image intensity is less significant than the local structural information of the images or in case of wide-baseline images where area-based methods based on the correlation of interest points are ineffective due to the large perspective effects. The most reliable and powerful feature detector and descriptor is the SIFT (Scale Invariant Feature Transform) operator [28]. SIFT extracts image features invariant to image scaling, rotation and (partially) invariant to illumination changes and camera viewpoint (affine transformation) and associates a descriptor with a dimension of 128.

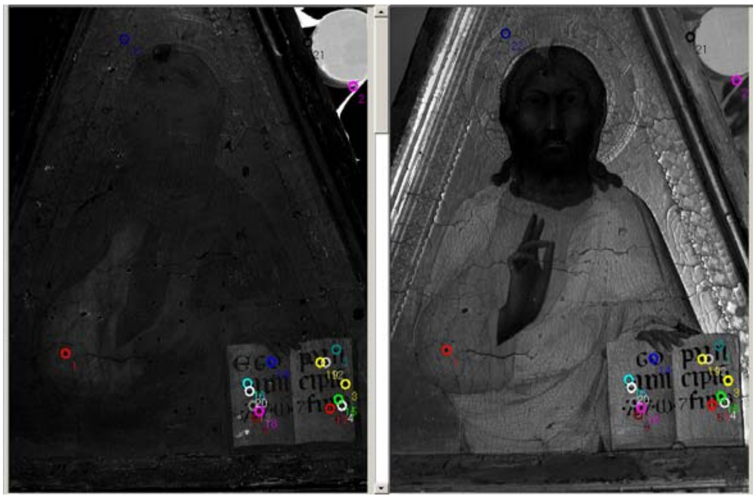
2.3. A novel 2D-2D automated registration method

Driven by our work in art diagnostics and multispectral image registration, a well known automated registration method based on image features was customized for multimodal images registration purposes. Although the previously described MMI approach is a very powerful and successful method for such kind of applications, our approach resulted in our trials faster and still reliable in aligning images with low amount of shared information. The developed registration works according to the two steps:

- Feature detection (salient regions) and correspondences establishment: regions are extracted and described using the SIFT method. In order to have a short processing time and nevertheless a good estimate of the transformation parameters required, the algorithm is set to work on a limited number of features.
- Transformation parameter estimation: the found correspondences are used to compute the transformation between the image pairs. A least squares estimation is employed to compute the affine or projective parameters and cope with possible outliers.

2.4. Results

We tested the methodology presented in Section 2.3 using different multimodal images. The multispectral acquisition system used (property of Art-Test, Italy [21]), associated with appropriate light sources, delivered a number of monochromatic images, one for each chosen transmission band, acquired in three different modalities: visible reflectance, IR reflectography and UV induced fluorescence.



- Calibrated UV induced fluorescence and IR reflectography images acquired using interferential filters in front of the camera objective, with peak transmissions respectively at fluorescence at 450 nm and at 900 nm.
- Numb. features: 21
- Transf. sigma0: 0.83 px

- UV induced calibrated fluorescence images acquired using an interferential filter in front of the camera objective, with peak transmissions respectively at 450 nm and at 750 nm.
- Numb. features: 10
- Transf. sigma0: 1.02 px

Figure 1: Examples of multispectral images of paintings, showing the extracted homologues features required to register the images for further art diagnostic analysis.

Despite the fixed and stable set-up, the use of multiple filters leads to multispectral images which are misaligned or scaled with respect to each other, due to the different optical path or a possible relative skewed position of the corresponding filters in the filter wheel or a slightly different distance of the acquisition system from the painting in the various measuring sessions. For these reasons, the acquired images needed to be precisely registered in order to provide aligned multispectral data which could be used e.g. to identify the different materials on the art works and therefore to allow material detection, classification, change detection as well as to ease virtual restoration and cleaning.

Figure 1 shows some results, reporting the extracted homologues points found by means of the SIFT detector/descriptor and the statistical quality of the least squares estimation used to determine the alignment parameters. The image correspondences and transformation parameters were quickly computed and the visual inspection of the overlapped image pairs did not reveal any misalignment.

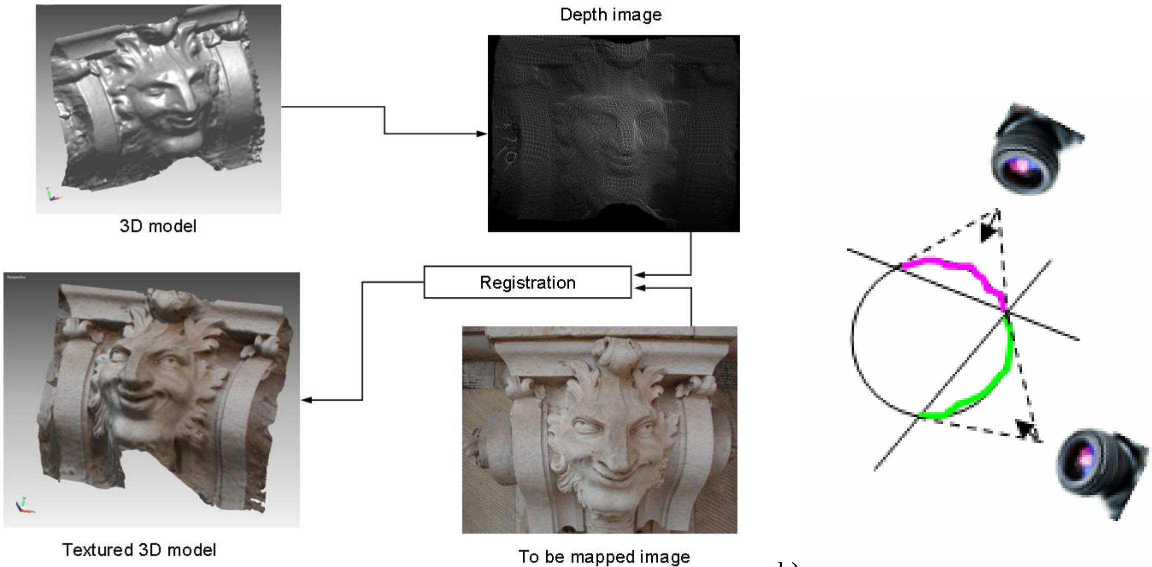
3. 2D-3D data registration

3D geometric models often need to be combined with 2D data for photorealistic visualization, GIS applications, etc. There are several methods to produce digital 3D models and usually they are selected according to project requirements, users experience, object's location and project's budget. The actual reality-based 3D modeling technologies involve mainly optical range-based active sensors [36], image-based passive sensors [37] or an integration of them [38], trying to exploit the intrinsic potentialities of each technique. The geometric 3D model which is derived is afterward generally textured for more realistic visualization. The texture mapping process is generally intended as the mapping of colour information onto the 3D data, which are in form of points or triangles (mesh). The texturing of 3D point clouds (point-based rendering techniques [39]) allows a faster visualization but for detailed and complex 3D models it is not an appropriate method. On the other hand, in case of meshed data, the texture is automatically mapped if the camera parameters are known (e.g. if it is a photogrammetric model) otherwise homologues points between the 3D mesh and the 2D image to-be-mapped should be identified (e.g. if the model has been generated using range sensors). This is the bottleneck of the texturing phase as it is still an interactive procedure and no automated and reliable approaches were proposed yet. Indeed the identification of homologues points between 2D and 3D data is a hard task, much more complex than image to image or geometry to geometry registration. Furthermore, in applications involving infrared or multispectral images, it is generally quite challenging to identify common features between 2D and 3D data. In practical cases, the 2D-3D registration is done with the well known DLT approach [40] (often referred as Tsai method [41]) where homologues points between the 3D geometry and a 2D image to-be-mapped are used to retrieve the intrinsic and extrinsic unknown camera parameters. The colour information is then projected (or assigned) to the surface polygons using a colour-vertex encoding or a mesh parameterization.

3.1. A novel 2D-3D automated registration method

A novel method for automated texture mapping of different typologies of 3D models has been developed. The registration method consists of two steps (see Figure 2):

- automated generation of a depth map image of the 3D model to produce an intrinsic mapping between depth map pixels and the corresponding vertices of the model
- registration of the depth map with the image to-be-mapped using the Mutual Information registration method (see par. 2.1).



a) b)

Figure 2: Sketch of the proposed method. a) From the 3D geometric model a depth map image is generated. This is automatically registered with any external image using the Mutual Information method and then mapped onto the 3D geometry for photo-realistic visualization. b) For the evaluation of the depth map values, according to texture image, a proper cut of the model is performed and the z-data needs to be referred to such cut plane.

3.1.1. Depth map generation

Starting from the geometric 3D model, a depth map is built as a two-dimensional array such that the x and y vertices coordinates of the model correspond to the rows and columns of the array (as in an ordinary image), and the corresponding depth readings (z values) are referred to a cutting plane and stored in the array's element value (see Figure 2). Such a map is thus a grey scale image where the z information is stored in the intensity information, being therefore a projection of the 3D coordinates into the x y plane. The so generated map intrinsically keeps an exact correspondence between 2D pixels and 3D vertices of the model. As the vertices of a 3D model are not usually placed along a regular grid, the projected depth map could have sparse values or holes. While the ratio between rows and columns of the map depends on the ratio between the x and y dimensions of the 3D model bounding box, its specific dimensions vary according to the chosen area of each entry/pixel. By associating at most one vertex per pixel, the pixel area is small and several pixels are “empty”, thus generating holes in the map where vertices are far away from their neighbours. On the other hand, by considering a bigger pixel area, more than one vertex could fall in the same pixel, thus leading the system to make a choice. The chosen strategy has been to select the vertex with greater depth value, since generally more representative of the details “emerging” from the surface. The 3D shape is highlighted by the depth map image, and is often related with some “visual” details depicted in the to-be-registered image: for example, a brushstroke offers both a 2D information, due to its colour or shading, and a 3D structure, due to its thickness. This relation is exploited for the following registration step, thus conveying the correspondence between the model vertices and the map pixels to the to-be-mapped image.

3.1.2. Depth map – texture registration

Since the synthetic depth map image is intrinsically mapped to the model, the registration of a different image with the map allows to convey the pixels-vertices correspondence to the new image, thus easily performing a texture mapping with the new image. The approach is to employ the Maximization of the Mutual Information (MMI) method, since it is a powerful and reliable method also when a low amount of information is shared between the two images. With such a registration method, the need of a manual identification of common points in the model and in the texture image is overcome. Since the process is completely automated, the accuracy depends on the MMI registration algorithm. The maximum MI will be reached when (i) the cut plane will be perfectly perpendicular to the camera position at the moment of the texture acquisition, (ii) the scale between model and texture will be the same and (iii) the relative translation and rotation agree. Therefore, the algorithm should try every possible position and for each position evaluate the MI. In order to obtain optimal results, the texture image should be undistorted, otherwise the registration algorithm should also evaluate the MI trying to compensate for the deformations of the texture image, at the price of a higher computational time of the algorithm.

3.2. Results

In order to demonstrate the effectiveness of the proposed method, we used several 3D models (produced with image matching [42] and range sensors) and textured them with different kind of images. Figure 3 shows two examples of a flat-like objects (a coin and a bass-relief), with the generated depth map and final textured 3D model.

Figure 3: Two examples (coin and bass-relief) of the automated texturing method, showing respectively the generated depth map, the image to-be-mapped and the textured 3D model.

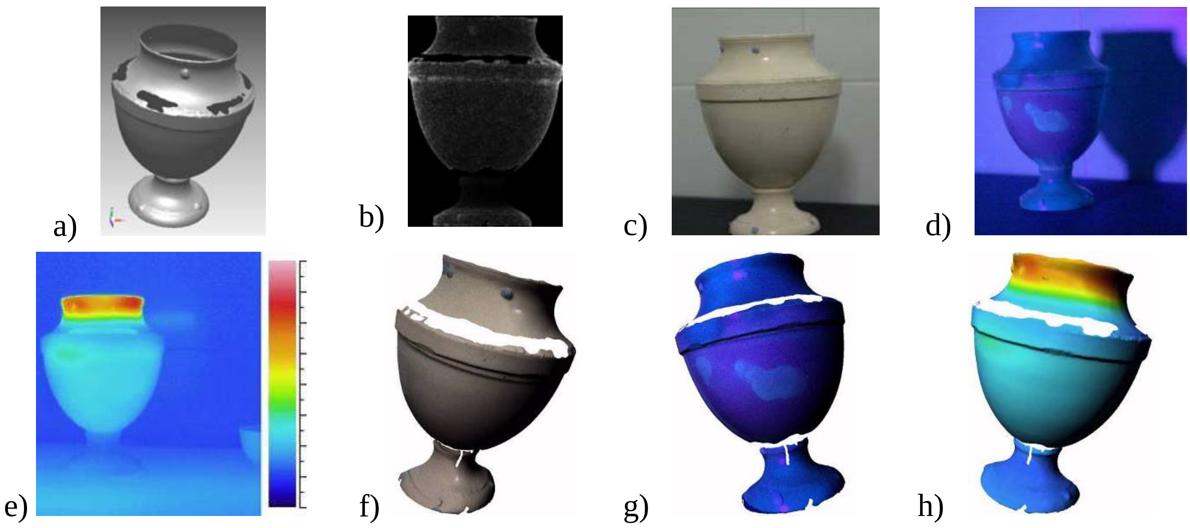


Figure 4: Texturing of a range-based pot 3D model (a): the range map (b) has been aligned with visible (c), UV-fluorescence (d) and near-IR (e) images for the successive mapping onto the 3D geometry. The generated textured models are shown in (f, g, h).

The proposed method was also tested with visible, IR and UV images (Figure 4), with more complex models. Visible UV Induced Fluorescence is an investigation technique able to highlight some features of art works, such as restored areas, which are often not easily distinguished to the naked eye. Texturing a 3D geometric model with fluorescence data enabled restorers to have a much more accurate map of the restored areas.

Figure 5 shows the texturing of a geometric 3D model using an authorized download Internet image. Despite the relatively little amount of information shared between the produced depth map and the image to-be-mapped, a proper registration was achieved.

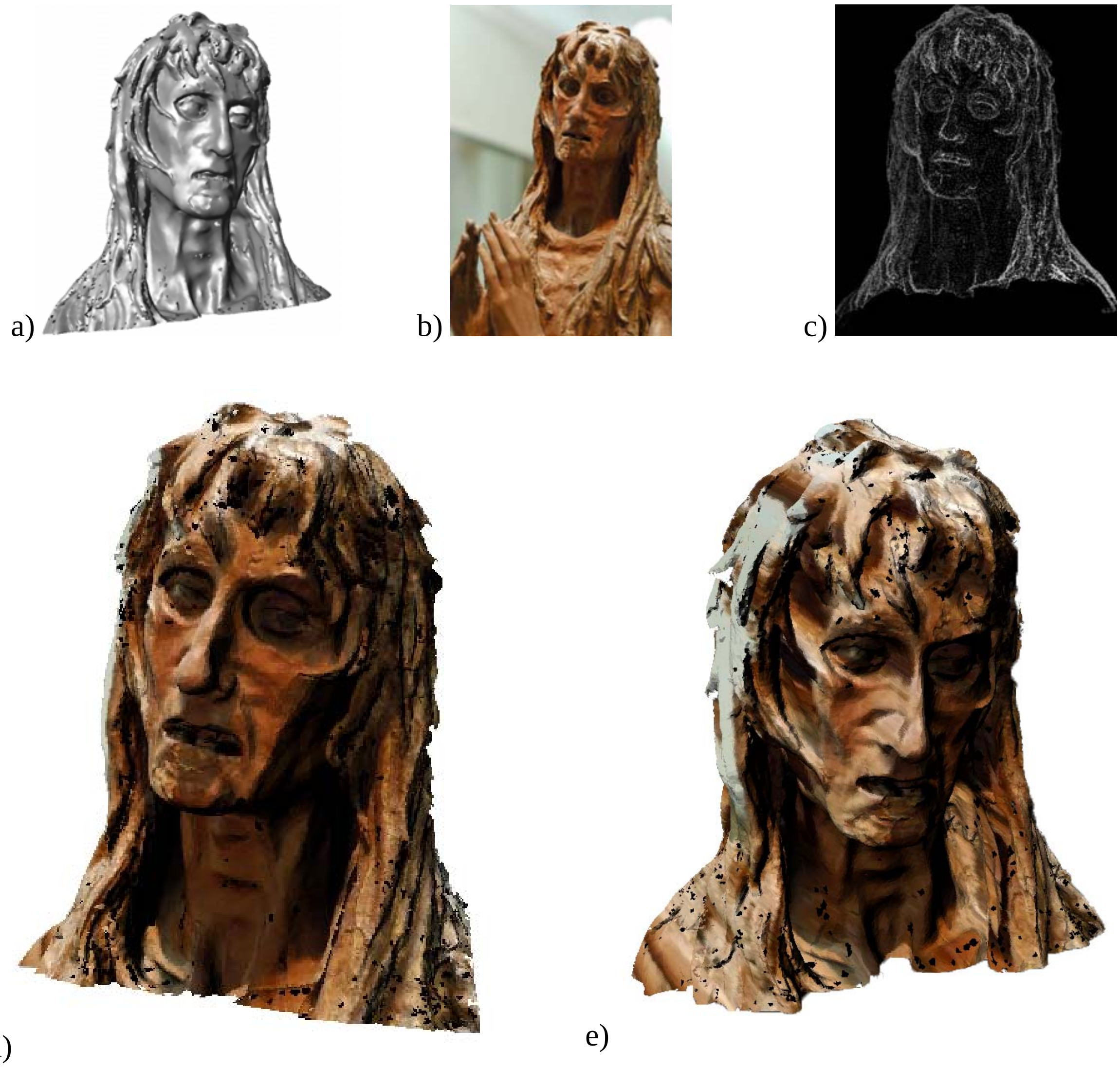


Figure 5: a) Screenshot of the geometric model of Maddalena's head [43]; b) An Internet image of the Donatello's sculpture; c) The computed depth map: please note the little amount of information shared with the texture image, which was nevertheless enough to accomplish a proper registration using the MMI criterion described in par. 3.1; d-e) Views of the textured 3D model obtained with the proposed method.

4. Conclusions and future works

The article reviewed the most employed registration techniques for optical and metrical applications related in particular to the Cultural Heritage field. Furthermore two new methods for the 2D-2D and 2D-3D data registration have been presented. The proposed methods overcome the need of a manual detection of common points between the data to be registered. Since the process is completely automated, the accuracy depends on the registration algorithm, while when manual detection is employed, the mapping precision achieved is very subjective. The proposed 2D-2D registration method speeded up the alignment of multimodal images although when the shared image content is very low, the MMI approach may be still more reliable. The 2D-3D registration method proved to be a very promising approach, succeeding in properly texturing even quite challenging examples, although more tests need to be done.

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