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Mutual Correspondences: an hybrid method for image-to-geometry registration

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Abstract

Image registration is an important task in several applications of Computer Graphics and Computer Vision. Among the large number of proposed approaches, currently there is no solution which is automatic and robust enough to handle any general case. The most robust methods usually require a significant intervention by the user to specify many 2D-3D correspondences, while automatic techniques often rely on strong assumptions about the quality of 2D and 3D data.
In this paper we present Mutual Correspondences, which is based on a minimization function which combines correspondences based and Mutual Information based approaches, and takes advantage of the strong points of both. Mutual Correspondences give the user the possibility to "guide" Mutual Information with only a few 2D-3D correspondences. The proposed approach results in a wider convergence range and in higher registration accuracy, regardless of the quality of both the image and the 3D model.
Mutual Correspondences were applied on some practical cases, where state-of-the-art approaches tended to fail, and they provided a mean to obtain accurate results. This led to a simple, robust and practical approach that can provide a way to register images in a few seconds.

Categories and Subject Descriptors (according to ACM CCS): Vision and Scene Understanding [I.2.10]: Intensity, color, photometry, thresholding—Three Dimensional Graphics and Realism [I.3.7]: Color, shading, shadowing and texture—Scene Analysis [I.4.8]: Shading—Digitization and Image Capture [I.4.1]: Imaging Geometry—Enhancement [I.4.3]: Registration—

1. Introduction

Image registration is a process in which an image is aligned to an existing 3D model. The alignment corresponds to an estimation of the (both extrinsic and intrinsic) camera parameters associated to the image. This operation is necessary in the context of several applications in the field of Computer Graphics and Computer Vision, and in most cases the accuracy of the result is key for the quality of the final data (colored models, 3D from images, geometry completion).
For this reason, several approaches to image registration have been proposed, but currently there isn't a solution which is fully automatic, fast and robust enough to be applied in the general case. Essentially, robust implementations require significant intervention by the user, while automatic and fast solutions work under strong assumptions on the quality and arrangement of the data.

This paper presents an overview of the main image registration methods, together with an analysis of their strong and weak points. Following this analysis, a new method, called Mutual Correspondences, is proposed.
Mutual Correspondences are based on the minimization function which is the result of the combination of two existing approaches: a Correspondences Based method and Mutual Information maximization. Correspondence based method is robust and flexible, but it requires a strong intervention by the user for picking/selecting the features. On the other side, Mutual Information is automatic and fast, but it works locally and it cannot be "guided" by the user.
Mutual Correspondences combine these two approaches, so that the number of correspondences chosen by the user (if needed) is strongly decreased. Moreover, a mechanism to widen the convergence range and constrain the Mutual Information to an accurate registration is provided. In this way,

the registration of an image can be completed in a semi-automatic way in a few seconds, without any kind of strong assumptions about the quality of the initial data.
The paper is organized as follows: the next section presents an overview of the main approaches in image registration. Section 3.2 schematizes the strong and weak points of the state-of-the-art approaches, and mathematically formalizes the Mutual Correspondences term. Section 4 shows some practical applications, where the use of other techniques didn't give satisfying results, in order to exemplify the improvements introduced by the proposed method. Finally, Section 5 presents the conclusions and the possible extensions of the approach.

2. Related work

The image registration methods can be divided in three groups: correspondence based, feature based and statistic correlation based. This Section will present some of the most important works in these groups, together with their strong and weak points.
Correspondences based methods. This group of methods strongly relies on an input given by the user. These methods follow an approach which is close to the one used in photogrammetry to reconstruct 3D objects: a set of 2D-3D correspondences is used to estimate the camera parameters by minimizing an error function. The methods use the same approach as the ones which aim is to calibrate the extrinsic or intrinsic of a camera (i.e. Zhang [Zha00]), but try to extend the approach to a generic situation instead of a calibration object. Their main differences are based on the applied camera model and the minimization function used. A well known and widely used approach was proposed by Tsai [Tsa87]: the estimation of camera parameters needs a set of at least 11 correspondences pairs. Other approaches [FT86] need a lower number of correspondences, but may be less robust and accurate.
While some works [FDG*05] try to reduce the needed time using image-to-image correspondences or automatic correspondences inference, these methods strongly rely on human intervention. Hence, the alignment process can be time consuming and demanding. Moreover, the alignment is obtained only on the basis of the input by the user.
Nevertheless, this kind of approaches is extremely robust, and thanks to the intervention of an user it is able to discriminate highly ambiguous situations: good results can be obtained regardless of image and geometry features and quality.
Features based methods. This group of method tries to extract features that are present on both the images and the geometry, and to fit them in order to estimate camera parameters.
Ikeuchi [IOT*07] presented an automated 2D-to-3D registration method that relied on the reflectance range image. In Neugebauer et al [NK99], the analysis of the image features is combined with the estimation based on correspondences.
But most of the features based works rely on the use of silhouette [BLS92, IY96, Low91, MK99]. In these works, the camera transformation is found by minimizing the error between the contour found in the image and the contour of the projected 3D model. Lensch [LHS00] proposed a robust implementation of previous silhouette based techniques, introducing a similarity measure to compare them. Moreover, the whole pipeline from registration to texturing was covered with very robust and almost automatic solutions.
A recent paper for 3D-3D and 2D-3D automatic registration [LSY*06] proposes an algorithm for a more general case, but under the assumption that the 3D scene contains clusters of vertical and horizontal lines. A robust extension for indoor environment was proposed by Li et al. [LL09], where the lack of features on large uniform surfaces are solved by projection of special light patterns to artificially introduce new features.
The features based methods all share similar strong and weak points: while usually fast and robust, they all work under the assumption that the needed features are present and easy to extract. For example, the silhouette methods require the entire object to be present in the scene, and sometimes a preliminary de-contouring of images is needed. For this reasons, features based methods are usually not applicable in a general case.
Statistic correlation based methods. These methods essentially try to estimate the camera parameters by analyzing the correlation between the image and a rendering of the 3D model. A widely used statistical measure is Mutual Information (MI). Proposed by Viola and Wells [VWMW97] and independently by Maes et al. [MCV*97], Mutual information has become a widely used method, especially for medical data. Several registration methods based on MI have been proposed: a comprehensive overview is presented in [PMV03].
A recent work by Corsini et al [CDPS09] extended the use of MI to a generic image registration case. This is obtained by using a illumination related renderings (ambient occlusion and specularity in addition the normal field proposed by Viola and Wells) of the 3D model. Results show that the approach is robust and fast, and the a registration can obtained regardless of the peculiar features of the object. Nevertheless, being a statistic based method, there is little possible intervention by the user to help the minimization process, and the global minimum of MI function, for a number of reasons, can be different from the best registration.
Two other recent exploitations of MI have been proposed for non-medical applications: 3D object tracking for simple template-based objects [PK08], and image registration improvement [CS07].

3. Mutual Correspondences

This Section will present the main idea of Mutual Correspondences. In the first part, the strong and weak points of all the above presented methods will be analyzed, and the intuitive idea of Mutual Correspondences will be given. The second part will present the mathematical formalization of the proposed approach, together with an analysis of the contribution of the terms which compose the minimizing function.

3.1. Mutual Correspondences: exploiting the strong points of image registration methods

The groups of approaches presented in the previous section can cover a wide range of possible cases, but each of them has different strong and weak points, which are resumed in Table 1. To summarize, correspondences based methods are very reliable, and very good results can be obtained even with low quality images or geometry, but they need a strong user intervention, both in terms of time and accuracy. Feature based methods are fast and precise, but they work under strong assumptions on object features, often require preprocessing on data and the convergence is dependent from the initial position of the model. Correlation/Statistic based methods are automatic, fast and quite robust, but the user has no control on the final result, so that if, for example, the geometry is not accurate, the final result could be not satisfying. Moreover, the convergence is dependent on the initial position.
While none of presented approaches provides an ideal solution, their strong and weak points are somehow complementary. Is it possible, for example, to exploit the strong points of the groups by integrating the robustness of correspondences methods with the user-friendly approach of the other two approaches?
With this aim, we created Mutual Correspondences (MC), which is a method integrating a correspondence based approach to the advantages of Mutual Information. We chose not to use Features based approaches for two main reasons: the strong assumptions on the objects shape and/or texture, which limit their generality, and the fact that MI methods implicitly exploit the information given by feature (i.e. the silhouette, see [CDPS09] for details).
Hence, the goal is to estimate the camera parameters by minimizing a term which contains a contribution from both MI and correspondences. In this way, only a few correspondences are necessary to guide the MI to a faster and more accurate convergence. In the next section, we will present the mathematical form of MC, together with some considerations on the advantages of the combination of the two approaches.

3.2. Mutual Correspondences term: definition and discussion

All the image registration methods can be formalized as a minimization (or maximization) of a multi-dimensional function, where the number of variables depends on the number of camera parameters, and the term to minimize is related to the peculiar approach. In our case, the function to minimize is a 7D one, since the goal is to estimate six term for the extrinsics (three for the position and three for the orientation of the camera in space) and one for the intrinsics (the focal length).
In the case of correspondence based method, the term to minimize is usually the average distance in pixels between the 2D image point and the correspondent 3D point projected on the image plane:

$$E(Cor,C) = \frac{\sum_{\forall cor_i \in Cor} \sqrt{(x_{p_i(C)} - x_i)^2 + (y_{p_i(C)} - y_i)^2}}{N} \qquad (1)$$
$$C = (\theta, \phi, \psi, t_x, t_y, t_z, f)$$

where:

(x_{p_i}, y_{p_i})	projected 2D point of the original 3D point of the correspondence
(x_i, y_i)	original 2D point of the correspondences
N	total number of correspondences
θ, ϕ, ψ	Eulero angles
t_x, t_y, t_z	components of translation vector
f	focal

When using Mutual Information, the aim is to maximize this value, which can be defined as:

$$MI_{(I_A, I_B)} = -\sum_{a,b} p(a,b) \log \frac{p(a,b)}{p(a)p(b)} \qquad (2)$$

where

I_A, I_B	images
$p(a,b)$	joint probability of the event (a,b)
$p(a)$	probability that a pixel of I_A gets value a
$p(b)$	probability that a pixel of I_B gets value b

Hence, the function to maximize is MI(I_A,$I_B(C)$) where I_A is an image to be calibrated and $I_B(C)$ is the a rendering of the model from the current camera position C. See [CDPS09] for further details.
In order to integrate the contribution of these two methods, we propose a very simple combination of them by defining *Mutual Correspondences* (MC) as:

$$MC_{(I_A, I_B, Corr, C)} = k(-MI(I_A, I_B(C)) + (1-k)E(Corr, C) \qquad (3)$$
$$C = (\theta, \phi, \psi, t_x, t_y, t_z, f)$$

MC is defined as a simple weighted sum of the two terms, where the k weighting value defines the amount of contribution of each term. The first remark that can be pointed out about this measure is the fact that we are dealing with different quantities: while one of the components is a (average) error in pixels, the other one is a pure number so this blending has to be make with a bit of care.
The intuitive idea behind the proposed idea is that MI could be "guided" by a few correspondences in the cases when the minimum in MI doesn't correspond to the best alignment. At the same time, a satisfying alignment could be reached with very few (not more than 4-5) correspondences instead of the

	Strong points	**Weak points**
Correspondences based	Robust and reliable	Time consuming
	Controlled by the user	Need for many accurate correspondences
	Independent from initial position	No contribution from geometry and image
Features based	Automatic	Accurate geometry and evident features required
	Precise	Strong assumptions on images
	Fast	Dependent from initial position
		Pre-processing often needed
Statistic correlation based	Automatic	No control on final result
	Precise and easy to use	Accurate geometry required for best result
	Fast (GPU implementation)	Dependent from initial position

Table 1: *Strong and weak points of image registration approaches*

number needed (usually from 15 to 20) to obtain a similar result with the correspondences based methods.

In order to have a visual cue of the improvement in convergence, it would be necessary to plot the shape of the function to be minimized. Unfortunately it is quite complex to visualize a 7D function: a possibility is to evaluate the shape of the MI function in the neighborhood of the optimal solution. Analogously to the visualization in [CDPS09], we scaled the image to 800 pixels in width and we obtained a reference registration with a high number of correspondences using a semi-automatic tool [FDG*05]. Since the MI function around the aligned position is a function of seven camera parameters, we explored the overall shape around the aligned position with 30 1D sections, calculated in random directions in the 7D space. These plots intuitively show how the error behaves when moving far from the optimal alignment.

Figure 1 shows an image registration example regarding a

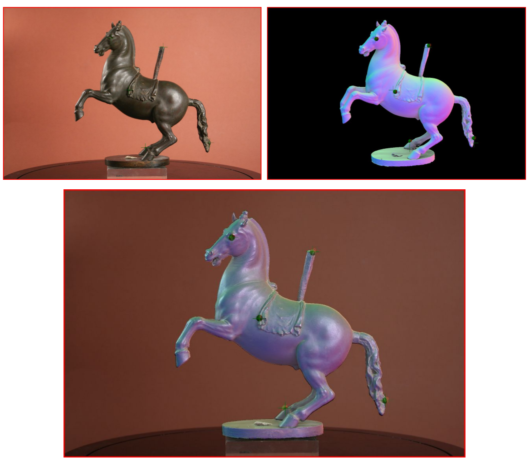

Figure 1: *Horse example: top, the image and a snapshot of the 3D model. Bottom, a snapshot of the reference alignment*

bronze horse: an accurate registration (Figure 1-right) can be obtained by manually setting at least 20 correspondences. An accurate result can be obtained using only MI, but if we analyze the shape of MI for 30 pixels around the reference (Figure 2), we notice a strong minimum in the center, but also the presence of several local minima, that can influence the convergence speed and accuracy (e.g. it is possible that some of these local minima 'trap' the minimization process).

Figure 3 shows the MC plot (k=0.9) in the same interval,

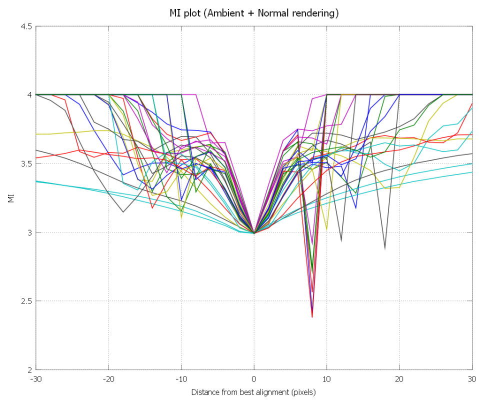

Figure 2: *MI shape around reference registration for Horse example*

obtained with 5 correspondences. It is clear that all the local minima around the reference have been removed, and the shape of the function shows a unique, very strong global minimum.

The plots show that the use of a few correspondences widens the convergence range, so that an accurate registration can be achieved almost regardless of initial 3D model position. This greatly improves MI robustness; moreover, correspondences can be a mean to "guide" the MI even for fine registration, as it will be shown in the next section.

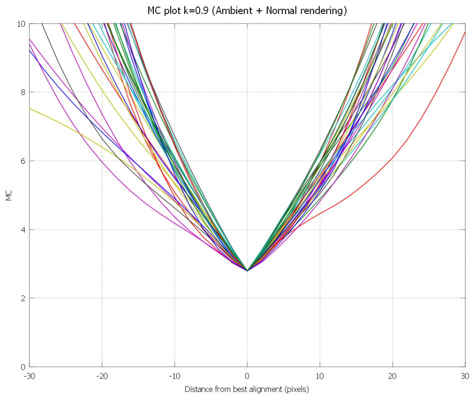

Figure 3: *MC shape (using 5 correspondences) around reference registration for Horse example*

Figure 4: *Horse example: top, the initial position. Bottom left: result after 225 iteration using MI. Bottom right: results after 225 iterations using MC.*

4. Results and discussion

In order to test the performance of the proposed method, a similar framework to the one used in [CDPS09] was created. The camera parameters are found by minimizing the MC value using the optimization algorithm NEWUOA, described in [Pow04], which uses quadrics to approximate a function.

The user has the possibility to manually set the correspondences and an initial position for the model, and to decide the value of k (Equation 3) to give different weights to the components. In this way, it is possible to evaluate the performances of MI (k=1) or correspondences only (k=0).

A first general remark is that the value of k does not influence the performances in the general case: all the results presented below were obtained using k=0.9. Different values of k could be useful in very peculiar cases, when the role of one of the contributions is fundamental.

The first example confirms the statement at the end of previous section: Figure 4 shows an example of registration for the Horse model. On top, the initial position, very far from the registered one, is shown. The bottom left snapshot shows the result of 225 iteration of the pure MI method, which was not able to converge to a good solution. The bottom right snapshot shows the result after 225 iterations of MC using 5 correspondences: the method was able to converge to an ideal solution. This shows that the convergence range of MC is extremely big, so that the whole method is very robust.

Another advantage of the proposed solution is the possibility to refine the registration by "constraining" the MI with a few correspondences. While MI performs very well for fine alignment, there are some cases where obtaining a good results is hard, if not impossible. This happens not only when one of the elements of the registration process (image or 3D model) is of low quality or incomplete, but also when there is little geometric detail, or the image exhibits a "distracting" background or repeating patterns.

We will show three examples where MC is able to improve the results of MI with a very low effort. For all the shown examples, an accurate registration can be obtained using correspondences based method, but with the need of at least 20 correspondences, and a consequent significant cost in time and attention by a skilled user. The accurate registration used as a reference for the graphs were obtained in this way [FDG*05].

The first example is shown in Figure 5: in this case a shepherd nativity statue was taken into account. The quality of both image and 3D model is above average, but the best registration with MI presents some misalignments (Figure 5,first row, middle). This can be due to a distortion in the image. Using MC, with 5 correspondences, the results is much more precise (Figure 5,second row, middle). The shapes of MI and MC plots (Figure 5,last column) confirm that the shape of the MC presents a much more defined minimum around best solution, while MI has several similar minima around it.

The second example regards a statue which was partially acquired using a time-of-flight scanner: hence, the accuracy of geometry in not very high. Moreover, the image to register presents a background which is very similar to the statue. For these reasons, the alignment with MI (Figure 6,first row, middle) is unsatisfactory, while MC obtain a good alignment, while not perfect due to the low initial geometry quality. Functions plots show that MI doesn't present a strong minimum around the best alignment, while MC uses the 5 correspondences to "guide" the minimization smoothly. In this case, even the alignment using correspondences was very hard, since it was difficult to find enough accurate correspondences on the inaccurate 3D model.

The third example (Figure 7) is about a small portion of the David of Michelangelo. This was part of a project to investigate a series of small fractures in the lower part of the monument by using a very accurate scanning of a portion of the ankle of the statue, and high quality images. The registra-

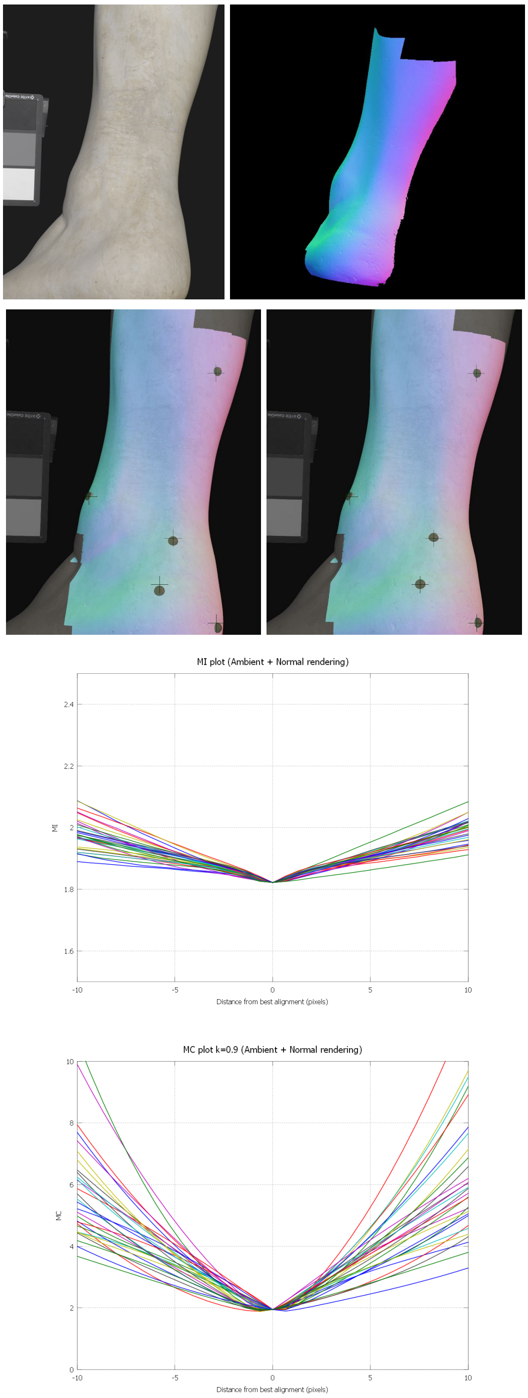

Figure 7: *David example. From top to bottom: original image and a snapshot of 3D model; Best alignment with MI and MC; MI shape around best alignment; MC shape around best alignment.*

tion must be extremely accurate. Unfortunately, the portion of 3D surface acquired was extremely small, and geometric features are present but hard to be spotted on the photos. In order to obtain an accurate registration using a pure correspondences methods, at least one hour of work is needed. The result of MI (Figure 7,middle row, left) is not accurate due to the lack of geometric features and the distracting silhouette (which is different from the real silhouette of the statue in the image). Using 5 correspondences, a very accurate registration is obtained with MC.
In conclusion, the use of MC represent a very effective blending between two approaches in image registration. The combination of the two terms widens the convergence range, and gives the possibility to "drive" the fine alignment in order to obtain an accurate registration even in the case of low quality, ambiguous or incomplete 3D and 2D data.

5. Conclusion and future work

The paper presented an innovative approach to image registration: two state-of-the-art methods are combined in a unique error function, which is minimized in order to estimate camera parameters.
The two approaches (Correspondences and Mutual Information) prove to be complementary in their strong and weak points. In this way, a semi-automatic image registration approach, where the input by the user is reduced to the setting of a few (usually two to five) correspondences, gives the possibility to align an images regardless of the quality and nature of both the 2D and the 3D data.
Mutual Correspondences has been integrated in a user-friendly application which will be made freely available for use, as a feature of existing freeware tools for mesh processing (i.e. Meshlab [CCC*08]).
Some possible extensions of the proposed work are:

- *Accurate testing using a ground truth*: due to the nature of the problem, there is no real numeric measure of the accuracy of camera calibration. The validation is usually based on visual control. It could be possible to create a "ground truth" test set, on the base of which all the state-of-the-art methods could be compared. Nevertheless, it is difficult to find such a general case that could exploit the strong points of all the approaches.
- *Further combination with existing techniques*: the proposed method could be further combined with existing techniques, in order to improve and fasten convergence. For example, if three or more correspondences are given, these can be used to provide an extremely precise starting point for the use of MC, by using a Levemberg Marquardt [Lou04] approach.
- *Automatic correspondences inferring*: the goal of registration methods is to be as automatic as possible: in order to improve MC, one direction could be to automatize correspondences setting by analyzing the rendering and the image, but also by exploiting the overlapping portions of

several images. For example, MI could provide an initial alignment, from which stereo matching techniques could be applied to improve registration.

- *Focal length estimation*: the estimation of focal length is one of the general issues in image registration, essentially due to numerical issues. A possible improvement in the method could be to find general and robust approaches to ensure rapid convergence in the estimation of this value.
- *Handling distortion parameters*: current MC implementation does not take into account the estimation of distortion parameters. A more accurate registration could be obtained by adding them to the set of estimated values.

In conclusion, Mutual Correspondences is a new, robust and easy to use approach to image registration. Its use can decrease the time needed for an accurate registration, and give a way to handle a wide range of practical cases.

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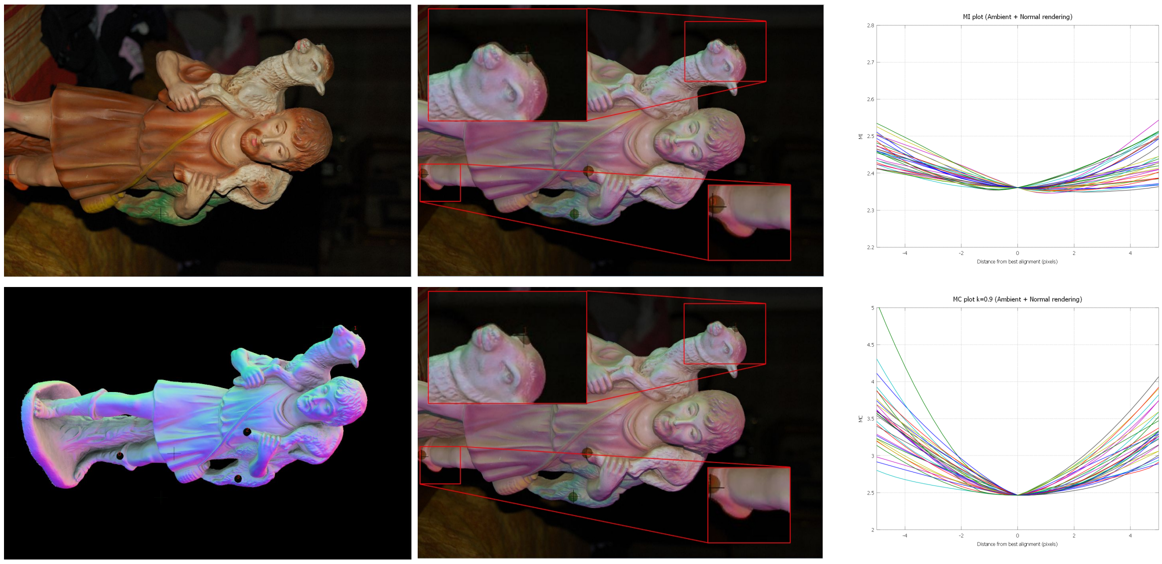

Figure 5: *Shepherd example. First row: original image, best alignment for MI, MI shape around best registration. Second row: a snapshot of the 3D model, best alignment for MC (5 correspondences), MC shape around best registration.*

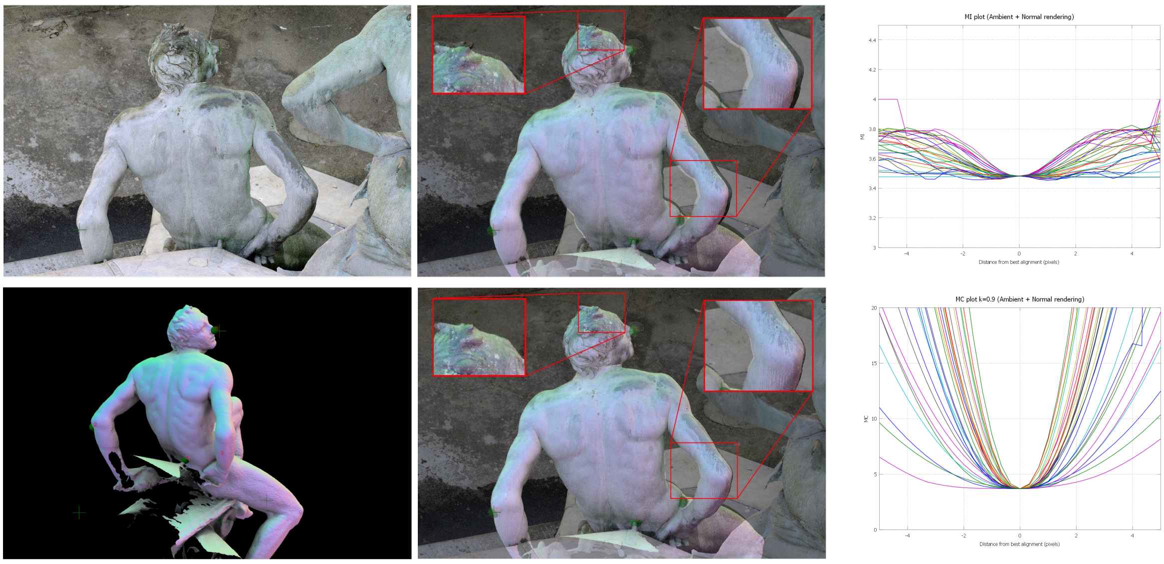

Figure 6: *Statue example. First row: original image, best alignment for MI, MI shape around best registration. Second row: a snapshot of the 3D model, best alignment for MC (5 correspondences), MC shape around best registration.*