Fuzzy Integral Imaging Camera Calibration for Real Scale 3D Reconstructions

Hector Navarro, Radu Orghidan, Mihaela Gordan, Genaro Saavedra, and Manuel Martinez-Corral

***Abstract*—In this paper, we present a quantitative analysis of the error in the reconstruction of a 3D scene which has been captured with Synthetic Aperture Integral Imaging system. The 3D information is obtained from 2D images for which the camera parameters are unknown. The model used for calibrating the Integral Imaging camera setup is based on fuzzy systems. These systems provide the opportunity for modeling of conditions which are inherently imprecisely defined. We demonstrate that the error in the 3D reconstruction not only depends on the number of cameras, but also to their relative positions. Our model is applied to a set of images captured experimentally from a real object. A true-color real scale 3D reconstruction is successfully achieved.**

***Index Terms*—Camera calibration, fuzzy system, integral imaging, 3D reconstruction.**

I. Introduction

INTEGRAL IMAGING (InI) is a 3D imaging technique that belongs to a broad class of multiview imaging systems. InI was initially proposed by Lippmann in 1908 under the name of Integral Photography [1]. Lippmann's technique consists of recording a set of 2D images, usually named as Elemental Images (EIs), from different perspectives to capture the spatio-angular information of a 3D scene. This can be done by inserting a microlens array in front of a light sensor or by using a camera array [2]–[4]. To form a particular perspective, each point belonging to the 3D scene is imaged onto the light sensor of the camera from a certain point of view. Note that although initially intended to work with visible light, it can be applied to other bands of the electromagnetic spectrum [5], [6].

Although InI can be also used to display 3D images, in this work we focus our efforts in performing real scale computational reconstructions of 3D objects. In the past years some methods have been proposed to perform volumetric reconstruction of 3D scenes and to obtain views from arbitrary directions [7]–[9]. The method proposed by Hong *et al.* in [10] is the most commonly used for computer reconstructions with InI. According to this method, in the reconstruction stage, each perspective is directly projected through a virtual pinhole array to reconstruct the 3D scene by superposition, conforming to geometrical optics. In order to minimize the error in the reconstructions, it is indispensable that the system is perfectly aligned during the pickup stage, or alternatively, it is necessary to carry out a calibration process. Some theoretical studies have analyzed the effects of the positional errors and positional uncertainty in InI systems [11], [12]. Two types of calibration procedures have been proposed: On the one hand, in explicit camera calibration, the calibration process ends up with a set of physical parameters of the camera. On the other hand, implicit calibration provides a set of rules that emulates the camera behavior without actually knowing the camera parameters. Explicit camera calibrations procedures have been previously applied to InI camera systems [13], [14], but to the best of our knowledge, implicit camera calibrations have never been applied to these systems. Orghidan *et al.* [15], have shown that the 3D reconstruction error achieved is drastically reduced by using a fuzzy calibration model but applied to a single stereo pair. Our intention here is to extend this technique to multiview InI.

In fact, to design an InI system, it is crucial studying the optimal configuration that minimizes the resources needed for its implementation. For building a camera array system, it is necessary to decide the minimum number of cameras needed to achieve the optimal trade-off between the accuracy of the 3D reconstructions and the economic investment made. Likewise, when using a Synthetic Aperture InI system (SAII) [16], it is elementary to reduce the number of movements of the camera. This saves time and diminishes the amount of data, shortening the computing time.

Thus, in this paper we study the performance of a SAII system calibrated using an implicit method based on fuzzy systems. The accuracy of the reconstruction is tested depending on the number of cameras employed in the pickup process. An optimal solution for the arrangement and the number of cameras necessary to minimize the error in the 3D reconstructions is presented.

The paper is organized as follows. In Section II we present the principles of a fuzzy inference system and the InI calibration scheme based on it. Section III describes the experimental setup employed for the calibration process. In Section IV we apply the calibrated InI system to reconstruct a real scale 3D object including color and texture. Finally, in Section V the main achievements of this paper are summarized.

II. InI Calibration Using Fuzzy Systems

The purpose of the calibration process is to establish a set of rules that allow obtaining the 3D coordinates of a point from its

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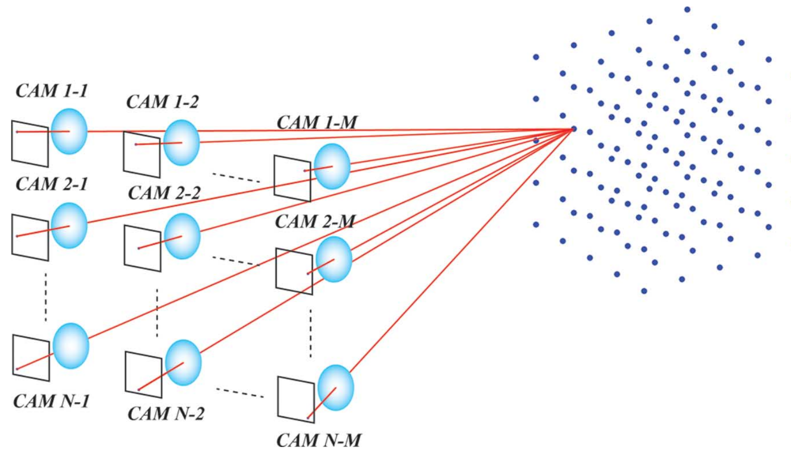

Fig. 1. Array on $N \times M$ cameras capturing a cloud of points whose 3D coordinates are known.

2D images captured in a multiview imaging system. To do this, we first need to generate a 3D point cloud whose positions are accurately known. Then, an array of $N \times M$ regularly spaced cameras, placed at fixed positions, captures different perspectives of the points in the cloud.

Then, we must find the points in one image which can be identified as the same points in the other images. As we are using a regular array, the correspondence problem is easily solved. Once the correspondences are known, each 3D point of the cloud is associated with its corresponding 2D coordinates over the sensors. This information is all we need to perform the InI camera calibration. No information on the position of the cameras or on their internal parameters will be necessary.

We will employ the method proposed in [15], where a Sugeno Fuzzy Inference System (FIS) is used for stereo calibration. A FIS [17], [18] is a system that uses fuzzy set theory to map inputs to outputs. It uses a set of rules called fuzzy rules which are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output. In the simple case that there are only two inputs x and y and one output z, a typical rule in a Sugeno fuzzy model has the form

$$z_i = a_i x + b_i y + c_i \tag{1}$$

where a_i, b_i and c_i are linear parameters for rule i of a model with N rules. These parameters are determined during the training process. The firing strength of each rule is computed as

$$\omega_i = \mu_{A_i}(x)\mu_{B_i}(y) \tag{2}$$

where A_i is a linguistic label and $\mu_{A_i}(x)$ is the membership function that specifies the degree to which the given x satisfies the quantifier A_i. The final output of the system is the weighted average of all rule outputs, computed as

$$z = \frac{\sum_{i=1}^{N} \omega_i z_i}{\sum_{i=1}^{N} \omega_i} = \sum_{i=1}^{N} \overline{\omega_i} z_i \tag{3}$$

When the normalized firing strength is defined as

$$\overline{\omega_i} = \frac{\omega_i}{\sum_{i=1}^{N} \omega_i} \tag{4}$$

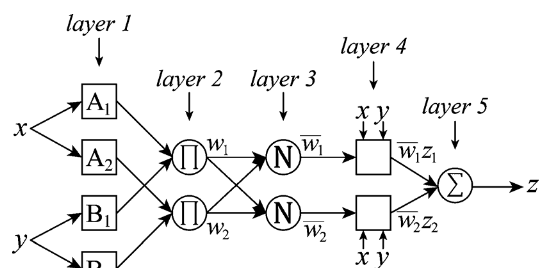

Fig. 2. ANFIS architecture of a fuzzy system with two inputs and with two rules.

There are several algorithms which can be used to automatically optimize the Sugeno FIS. We decided to use the adaptive neuro-fuzzy inference system (ANFIS) [19], which adapts the parameters of the FIS using neural networks. It applies a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership function parameters to emulate a given training data set. For the sake of simplicity, let us consider that the previously mentioned fuzzy system with two inputs and one output has only $N = 2$ fuzzy rules. The corresponding equivalent ANFIS architecture can be represented by the diagram in Fig. 2.

There are five layers of logic in the ANFIS model diagram. A circle indicates a fixed node, whereas a square indicates an adaptive node. The first layer is the *fuzzification* layer. A clustering algorithm will decide the initial number and type of membership functions to be allocated to each of the input variable. In the second layer each node calculates the firing strength of the corresponding rule. The third layer calculates the ratio of every rule's firing strength to the sum of all rules firing strengths. The output of this layer is directly the normalized firing strength obtained in (4). The adaptive nodes in layer four perform two tasks: the combination of the incoming rule antecedents and determining the degree to which they belong to the output linguistic label. The number of nodes in this layer will be equal to the number of rules. The fifth layer is the *defuzzification* layer. The single node in this layer computes the overall output as the summation of all incoming signals.

For applying this technique to our reconstruction problem we involve three fuzzy logic systems, one for each dimension of

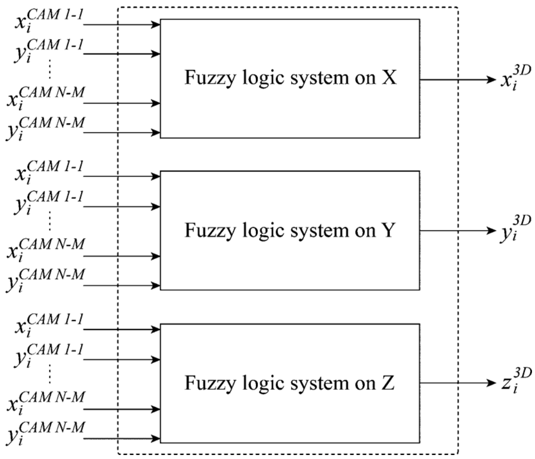

Fig. 3. Implicit camera calibration scheme based on our fuzzy model.

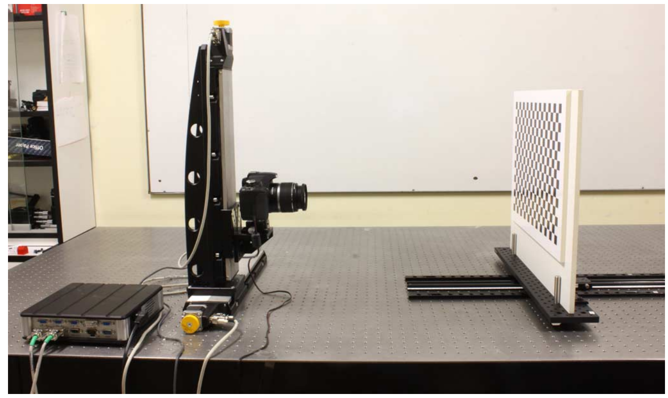

Fig. 4. SAII setup for capturing different perspectives of the checkerboard pattern employed during the calibration process.

the 3D space. Each of these fuzzy logic systems takes as an input the 2D coordinates of the corresponding points on each EI. The outputs of the fuzzy systems are the coordinates of the reconstructed points in the 3D space. The general block diagram is shown in Fig. 3.

The mean 3D error, ε_{3D}, obtained using the fuzzy calibration system can be calculated as

$$\varepsilon_{3D} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left((\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2\right)} \tag{5}$$

where n is the number of points in the cloud, $\hat{x}, \hat{y}$ and $\hat{z}$ are the Cartesian coordinates of a point estimated by the fuzzy system and x, y and z are the Cartesian coordinates of such point measured experimentally. Additionally, the mean error of each Cartesian coordinate, $\varepsilon_x, \varepsilon_y$ and ε_z, can be computed as

$$\begin{aligned} \varepsilon_x &= \frac{1}{n}\sqrt{\sum_{i=1}^{n}(\hat{x}_i - x_i)^2} \\ \varepsilon_y &= \frac{1}{n}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \\ \varepsilon_z &= \frac{1}{n}\sqrt{\sum_{i=1}^{n}(\hat{z}_i - z_i)^2} \end{aligned} \tag{6}$$

III. Experimental Setup

As stated in the previous section, for the calibration process it is necessary to generate a 3D point cloud whose positions are accurately known. To do this, we used a planar checkerboard pattern. Checkerboard internal corners are defined as special conjunction points of four alternating dark and bright regions. The inner checkerboard corners define a grid of points which can be automatically tracked. There is a wide range of existing algorithms for detecting regular grids in the images of calibration patterns. In our problem we have used the Harris Corner detector [20], which fits our needs perfectly. The checkerboard pattern was composed of 21×15 squares of 20 mm×20 mm. It was printed on adhesive vinyl and stuck on a foam board substrate. The area covered by the grid was 420 mm×300 mm. Hereafter we will refer to this checkerboard as “checkerboard A”.

For capturing the images of the checkerboard from different perspectives, instead of using an array of cameras, we used the SAII method (see Fig. 4). For a given distance of the checkerboard to the camera, we captured a set of 3×2 EIs. The pitch in the horizontal direction was 110 mm, and the pitch in the vertical direction was 120 mm. Then, the checkerboard was moved axially in steps of 10 mm for a total of 41 different positions. For each axial position, a new set of 3×2 EIs was captured. The grid of points consisting of the corners of the squares of the checkerboard A defines a volume of dimensions 420 mm×300 mm×400 mm. This volume constitutes the training volume of the fuzzy system.

From the captured images, we extracted the 2D positions of the grid corners over the camera sensor for each camera position and for each axial position of the pattern. These positions, together with the coordinates of the grid corners in the 3D space, constitute the training set of input-output data that we use for training the fuzzy system. After the training process, the fuzzy system is able to calculate the 3D position of a given point using as an input the correspondences of its 2D coordinates over the camera sensors.

To test the 3D reconstruction accuracy, we used another checkerboard pattern (checkerboard B) with the same number of squares as the checkerboard A (21×15), but the size of the squares was 15 mm×15 mm. The checkerboard B was moved axially in steps of 60 mm inside the training volume for six different axial positions. The process of the corner extraction was carried out for each camera position and for each axial position. The correspondences between points obtained for the checkerboard B were used as an input for the calibrated InI fuzzy system.

We wanted to quantify the error depending on the number of camera positions employed in the pickup process. The grid on which the camera was actually located was predefined, but we selected different subsets of camera positions. In this way, we considered different number of locations and also different relative positions.

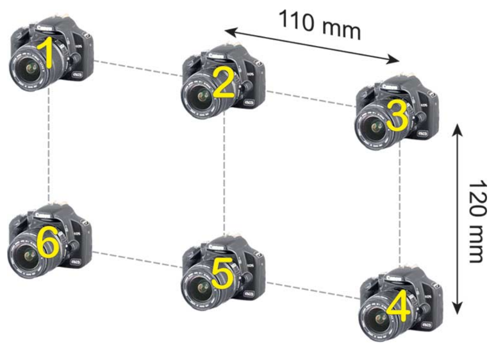

Fig. 5. Camera arrangement used for calibrating the fuzzy system and for capturing the information of a 3D scene.

TABLE I

Camera #	ϵ_{3D} (mm)	ϵ_x (mm)	ϵ_y (mm)	ϵ_z (mm)
1, 2	6.40	0.24	0.39	6.34
1, 3	2.56	0.23	0.29	2.49
1, 5, 3	3.32	0.27	0.19	3.26
6, 2, 4	3.23	0.26	0.21	3.27
1, 3, 4, 6	0.69	0.25	0.19	0.55
1, 6, 5, 4, 3	0.98	0.22	0.18	0.88
6, 1, 2, 3, 4	1.02	0.22	0.18	0.92
1, 2, 3, 4, 5, 6	0.83	0.24	0.19	0.71

Reconstruction error depending on the number of cameras employed in the calibration and their relative location over the grid.

The position of the cameras over the grid is denoted by a number ranging from one to six as shown in Fig. 5. Among the possible combinations that enable the experimental setup, we selected eight different arrangements for training the system. The performance of each arrangement was tested with the images of the checkerboard B captured from the same camera positions used for calibration process. The 3D position of the grid of points defined by the checkerboard B was calculated by the fuzzy system for each arrangement. These positions were compared with the actual 3D position of the grid points measured during the experiment.

IV. Calibration Results

Table I shows the error obtained using the fuzzy calibration system depending on the number of cameras employed in the calibration and their relative position over the grid. The mean 3D error, ε_{3D}, is calculated according to (5) and the mean error of each spatial coordinate, ε_y, ε_y and ε_z, is calculated according to (6).

As it can be seen in Table I, the accuracy of our method depends on the number of camera positions employed and also to their relative locations. From these results, we can draw a number of conclusions. Considering only two camera positions, as the horizontal distance between them is increased, the error in the axial coordinate is reduced. If we add one or more camera locations in the vertical direction, the error in this direction is also reduced. Optimum results are achieved by using four camera positions separated by the maximum achievable distance in the pre-established array. Adding intermediate camera positions in the array does not decrease the 3D error. By contrast, the error slightly increases.

Whereas increasing the number of cameras can be expected to lead to a more complex model and therefore increase the modeling accuracy, ANFIS is known to suffer from the "curse of dimensionality" as the number of inputs gets larger, caused primarily by the exponential increase in the number of fuzzy rules and parameters to be tuned during the learning process. From a practical point of view, if the number of inputs becomes larger than (usually) 8, the training time increases very much and, more importantly, the size of the training data needed for an accurate estimation of the fuzzy sets parameters needs to increase exponentially as well. Otherwise, the model parameters cannot be estimated with a good accuracy, and the result is a larger error than with an ANFIS model with less input variables. Such a case is also mentioned in other practical studies, such as that conducted by Castellano *et al.* in [21]; in which case, the results are similar to our findings. To some extent, subtractive clustering can alleviate the curse of dimensionality by reducing the number of fuzzy rules in the FIS structure; however this is only true for a limited number of input variables, generally not exceeding 8, which explains why most works in the field restrict to the use of ANFIS with at most 6 input variables which in our case would correspond to a system of 3 cameras; however our system proves the smallest error for a number of 4 cameras, corresponding to 8 input variables.

Although the results obtained are reflected in a quantitative manner in the previous table, Fig. 6 may help the reader to visualize the improvement achieved by using an InI system instead of a stereo pair. Blue asterisks mark the measured 3D position of the points over the grid and red crosses indicate the calculated position of those points by using the fuzzy system. As an example we show the reconstruction obtained with camera positions 1 and 2 (maximum error), and the reconstruction obtained with camera positions 1, 3, 4 and 6 (minimum error).

These results demonstrate the capability of the system to perform a real scale 3D reconstruction of a cloud of points with an average error less than 1 mm. The natural consequence of this ability is applying fuzzy systems to reconstruct a volume object.

V. 3D Reconstructions

Next, we checked the ability of the system to reproduce a real 3D object including its color and texture. To do so, first, the object was placed inside the training volume of the system. Then, the camera captured this object from different perspectives, with the same period and the same number of images used during the training process. From the previous analysis on system performance, it seems logical to use the configuration and number of camera positions that provide the best 3D reconstruction accuracy achieved. This configuration was compared with the one that provides the worst 3D reconstruction accuracy. Therefore, the first reconstruction was carried out from the fuzzy system that was trained for the camera positions 1, 3, 4, and 6 and the second reconstruction was conducted employing the fuzzy system calibrated for camera positions 1 and 2. In Fig. 7 we show the experimental setup used for capturing a 3D object located inside the training volume of the fuzzy system.

As a 3D object we used a mortar of known dimensions (see Fig. 8). The real size of the object can be compared with the size of the reconstructed object.

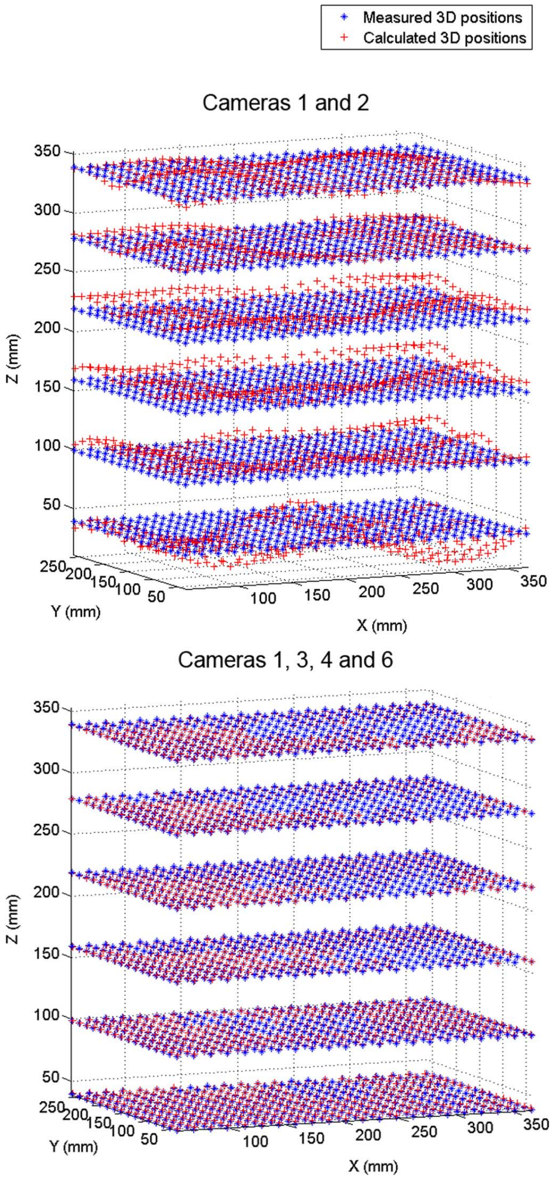

Fig. 6. Computational reconstruction of the cloud of points defined by the checkerboard B for six different axial positions inside the training volume. Reconstructed points are compared with the measured positions of those points.

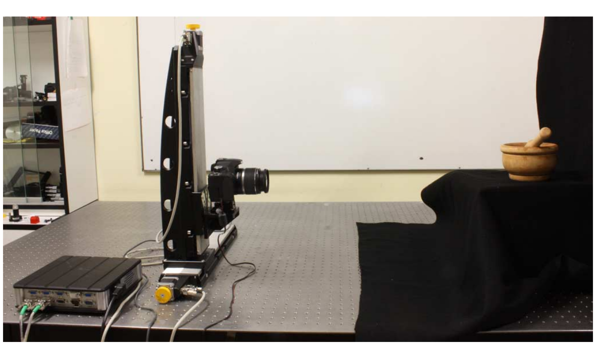

Fig. 7. Experimental setup for capturing different EIs of a 3D object. The mortar is located inside the training volume of the fuzzy system.

For the first configuration, the camera took four EIs containing different perspectives of the mortar from the camera positions 1, 3, 4, and 6 (see Fig. 9). But these images could not be

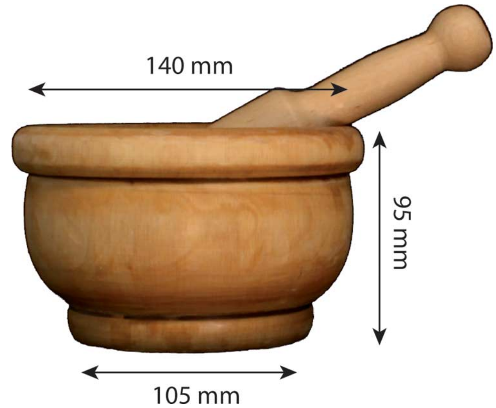

Fig. 8. Measured dimensions of the mortar employed as a 3D object.

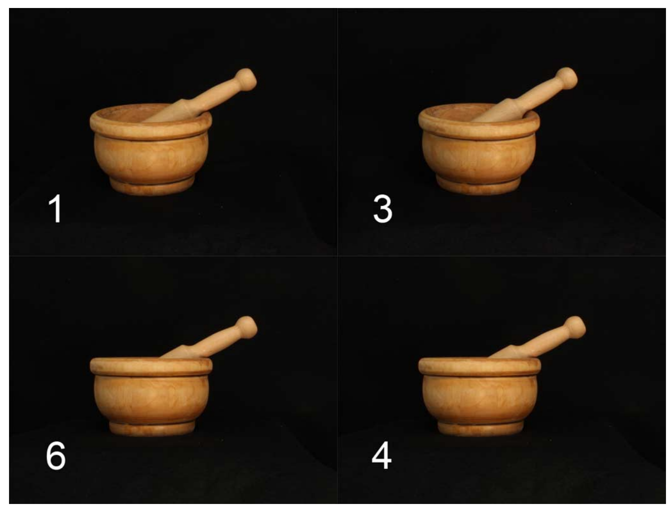

Fig. 9. Set of EIs captured with the SAII system. Perspectives correspond to camera positions 1, 3, 4, and 6.

directly employed by the fuzzy system. We first needed to establish the correspondences between each of the captured images. To do this, we used a stereo matching technique based on correlation. The basic stereo matching algorithm consists of choosing a specific block in a certain image and defining another block of pixels, called window, in the corresponding image. During the matching process, the window is moved along the corresponding image to find the block which holds a minimum difference of intensity with the specified one [22]. This disparity estimation was ameliorated by incorporating subpixel estimation [23] and dynamic programing [24] in the algorithm.

From the disparity map it was possible to obtain the 2D coordinates of every point of the surface of the 3D object over the sensor for the captured four views.

The fuzzy system used the correspondences calculated for the set of 2D photographs to obtain the 3D coordinates of the surface of the object. In Fig. 10, we show some of the reconstructions obtained with the fuzzy system rendered from different perspectives. As seen in this figure, in the reconstructions there are some errors. Firstly there are areas of the surface of the mortar with holes. These holes are due to how the clustering algorithm works. To obtain the 3D coordinates of a point, it is necessary that such point has been captured simultaneously by all cameras used during the capture process. When some parts are

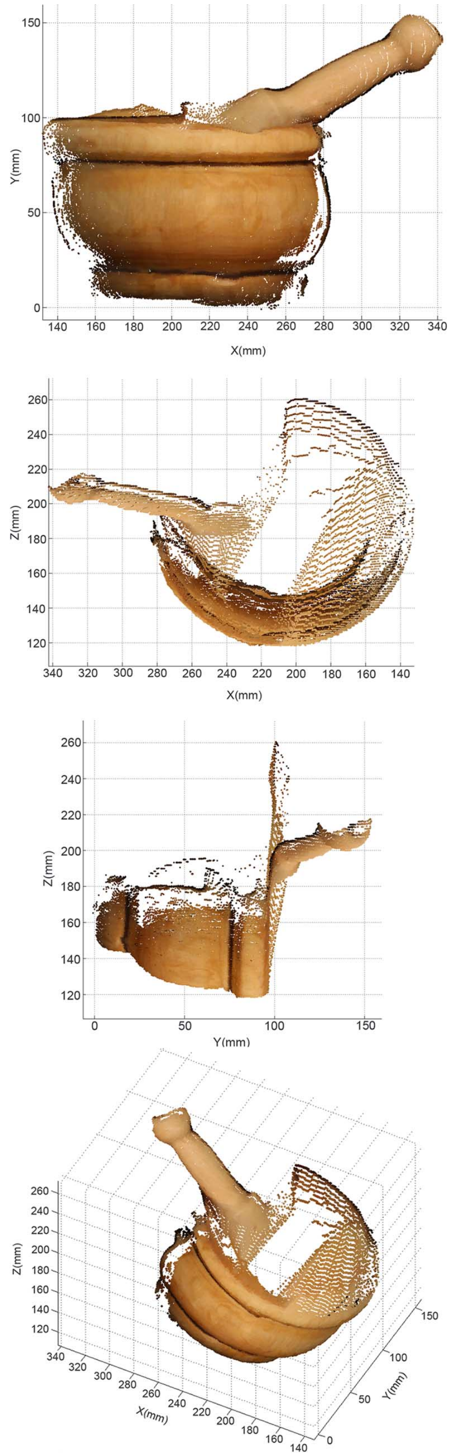

Fig. 10. Computational reconstructions of the mortar rendered from different perspectives. The fuzzy system has been calibrated using camera positions 1, 3, 4 and 6.

occluded for one or more cameras, the algorithm is not able to estimate the correspondences for such points, and an empty area appears in those parts during the reconstruction. Similarly, some artifacts appear on the top of the mortar, which is an area with occlusions in the vertical direction (see perspectives in Fig. 9). This cause the fuzzy system performs an interpolation when estimating the depths of those points, producing erroneous depth estimation.

Fig. 11. Stereo pair captured with the SAII system. Perspectives corresponding to camera positions 1 and 2.

Despite the errors in the reconstructions, reconstructed object dimensions correspond to the actual dimensions of the original objet. In Fig. 10 multiple views of the reconstructed object are shown. Cartesian coordinate systems in which the different views are represented, are graduated in mm so that measurements can be taken to compare the dimensions of the reconstructed object with the dimensions of the real object. In the front view reconstruction (plane XY), the height and the diameter of the base and the top of the mortar can be easily measured. Even though the measurement accuracy is not high because of some edges are not sharp, the diameter of the base of the mortar can be measured as to be 105 mm, while the diameter of the top of the mortar is close to 140 mm. The height of the mortar is about 95 mm. These measurements are good approximations to the correct size and proportions of the original object.

For the second configuration, the camera captured two EIs containing different perspectives of the mortar from the camera positions 1 and 2 (see Fig. 11).

After establishing the correspondences for the stereo pair with the same method than in the first configuration, the fuzzy system used such correspondences to obtain the 3D coordinates of the surface of the object. In Fig. 12, we show the reconstruction of the mortar calculated from the images captured from camera positions 1 and 2. The comparison of the reconstructions obtained in Fig. 10 with those obtained in Fig. 12, illustrates the improvement in the quality of the reconstruction with a multiple camera, compared with that from a two camera system.

VI. Conclusion

A fuzzy system was employed to calibrate a SAII system. The fuzzy system was calibrated for eight different configurations of the camera positions on a predefined array of locations. The error in the reconstruction process was quantified for different number of camera positions and also by changing their relative locations in the array. As expected, we found out that for a stereo pair, as the baseline was longer, the axial error was reduced. Adding a third camera position in the direction perpendicular to the baseline provides extra information to the system and hence reduces the reconstruction error in that direction. The minimum error was achieved with four camera positions located in the corners of the array. Adding camera locations in intermediate positions was expected to improve the resolution, but that was slightly worsened. From a practical point of view, if the number of inputs becomes larger than (usually) 8, the training time increases very much and, the size of the training data needed for an accurate estimation of the fuzzy sets parameters needs to increase exponentially as well. Otherwise, the model parameters cannot be estimated with a good accuracy, and the result is a

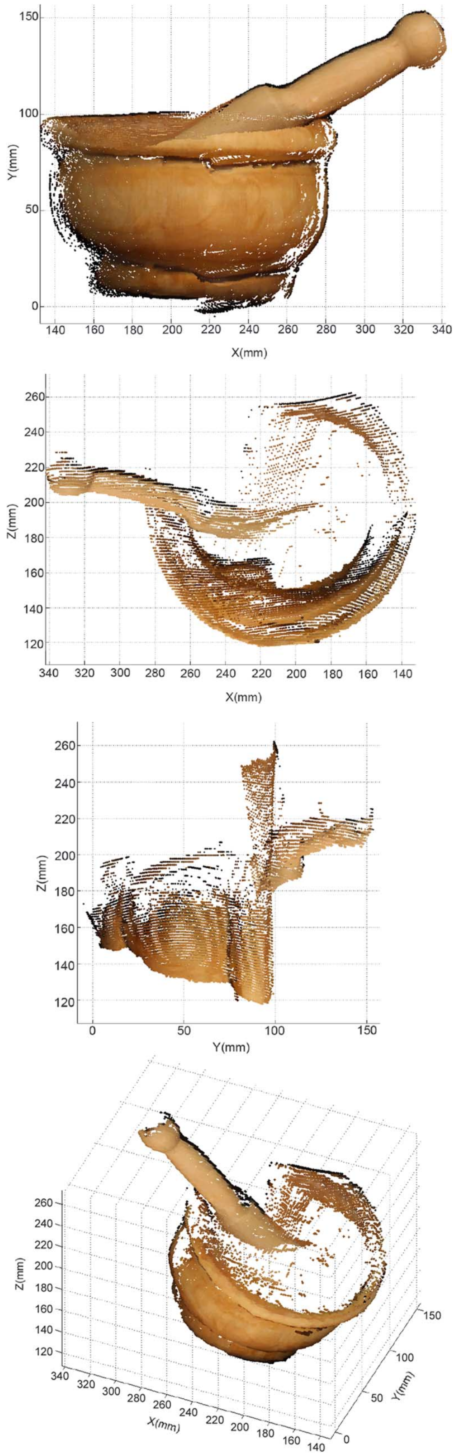

Fig. 12. Computational reconstructions of the mortar rendered from different perspectives. The fuzzy system has been calibrated using camera positions 1 and 2.

larger error than with an ANFIS model with less input variables. A solution for investigating the behavior of the system for more inputs would be either to use hybrid learning architectures (e.g., Genetic Algorithms—ANFIS), either to increase the training set significantly. However the second solution may not be the best option for a practical calibration system. The investigation of the first proposed solution will make the object of our future research.

The ability of the system to perform real scale 3D reconstructions including color and texture has been demonstrated by applying the fuzzy system to a real object. Reconstructions rendered from different viewpoints show the spatial accuracy of the proposed method. This calibration process can be used with SAII but it can be also applied to camera arrays. In general, SAII is a useful tool to partially occluded object reconstruction. The algorithm used in this article is not able to remove occlusions since the fuzzy system is trained so that the image of a point should appear in all EIs to get their 3D coordinates. Further research is needed to clarify if the algorithm can be trained to reconstruct scenes with partial occlusions.

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