Multi-view reconstruction for projector camera systems based on bundle adjustment

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Abstract

Range scanners using projector-camera systems have been studied actively in recent years as methods for measuring 3D shapes accurately and cost-effectively. To acquire an entire 3D shape of an object with such systems, the shape of the object should be captured from multiple directions and the set of captured shapes should be aligned using algorithms such as ICPs. Then, the aligned shapes are integrated into a single 3D shape model. However, the captured shapes are often distorted due to errors of intrinsic or extrinsic parameters of the camera and the projector. Because of these distortions, gaps between overlapped surfaces remain even after aligning the 3D shapes. In this paper, we propose a new method to capture an entire shape with high precision using an active stereo range scanner which consists of a projector and a camera with fixed relative positions. In the proposed method, minimization of calibration errors of the projector-camera pair and registration errors between 3D shapes from different viewpoints are simultaneously achieved. The proposed method can be considered as a variation of bundle adjustment techniques adapted to projector-camera systems. Since acquisition of correspondences between different views is not easy for projector-camera systems, a solution for the problem is also presented.

1. Introduction

Range scanners using projector-camera systems have been studied actively in recent years as methods for measuring 3D shapes accurately and cost-effectively. In these systems, a target scene is captured while it is lit by special patterns of light. From the captured patterns, correspondence between pixel locations of the projector and the camera is obtained. Since the geometrical structure of a projector can be regarded to be the same as a camera in such systems, 3D reconstruction is achieved from the correspondences by using a triangulation method. By coding locations of projector pixels into projected patterns, accurate correspondences can be obtained in pixel or sub-pixel accuracies. Thus, dense and precise 3D shapes can be captured.

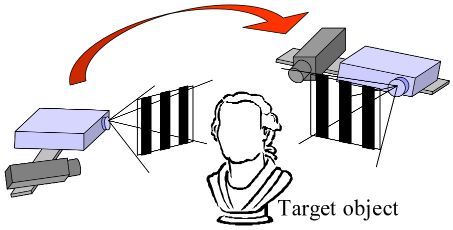


Figure 1. Entire shape scanning by moving a projector and a camera freely without calibration process.

Using these types of range scanners, only object surface that is observable from both the projector and the camera can be captured. Therefore, to acquire an entire 3D shape of an object, the shape of the object should be captured from multiple directions. The set of captured shapes should be aligned correctly to be integrated into a single shape model. A typical algorithm to align the captured 3D shapes is ICP algorithm. In this algorithm, two processes are executed iteratively; one is a process of searching corresponding points between overlapping regions of the shapes, and the other is a process of minimizing the distances between the searched correspondences by moving each of the captured shapes.

However, in real projector-camera systems, the intrinsic and the extrinsic parameters of the system have certain levels of errors. Due to these errors, the captured shapes are distorted. Thus, there remains gaps between the captured shapes, even after they are aligned with ICP algorithms. Such gaps cause several severe problems, e.g. failure in shape integration and blurring effect on texture.

In this paper, we propose a simple method to capture an entire shape with high accuracy using active stereo systems which consists of a projector and a camera. The basic idea is to apply multi-view reconstruction technique to a active stereo system and proposes a method for simultaneous estimation of extrinsic parameters of the active stereo system, motion parameters of different views, and 3D shape of the scene. Since a projector can be regarded as an inverse camera in these types of systems, it has been pointed out that its geometrical properties are the same as those of the camera [14]. Therefore, the proposed method can be considered as a variation of bundle adjustments for camera systems to projector-camera systems, in which motion parameters of the projector-camera pair, extrinsic parameters, intrinsic parameters and 3D positions of points are simultaneously refined. Note that there is a paper to solve the problem without assuming specific range scanner [4], however, our method is much simpler and stable for a procam system.

Actual scanning process is as follows. First, scan a target object by moving the projector-camera pair to cover the entire shape as shown in Figure 1. At each motion, active stereo method is applied to reconstruct the shape. Then, an initial registration is applied by manual or using image features. Finally, a modified bundle adjustment method for projector camera systems is conducted to retrieve the final result.

Note that the correspondences between different views can be acquired stably by tracking feature points for cameras, whereas, it is difficult for projector-camera systems because a projector is an inverse camera and cannot capture an image. To deal with this problem, the paper introduces a method that regards a 3D point of one view as corresponding to the closest points on reconstructed shapes from different views. Then, a modified bundle adjustment is applied to these correspondences for simultaneous estimation of the intrinsic and extrinsic parameters of the projector-camera pair, the motion parameters, and the shapes from all the viewpoints (The difference of the modified bundle adjustment used in the proposed method from the normal bundle adjustment is that the relative position between the projector and the camera is fixed, whereas there are no such constraint for the normal bundle adjustment). New correspondences are then estimated from the resulting shapes. The process is repeated until a residual error stop decreasing.

The contributions of the proposed system are as follows:

1. By moving the projector and the camera with a fixed relative positions by using, for example, a projector-camera rig, entire shapes of textureless objects or large scenes can be captured densely and accurately.

2. By applying bundle adjustment for projector camera systems, motion parameters between multiple viewpoints and extrinsic and intrinsic parameters of the projector-camera system can be simultaneously estimated.

3. The method to estimate precise correspondences between shapes measured from different viewpoints, which are difficult to acquire directly with projector-camera systems, is presented.

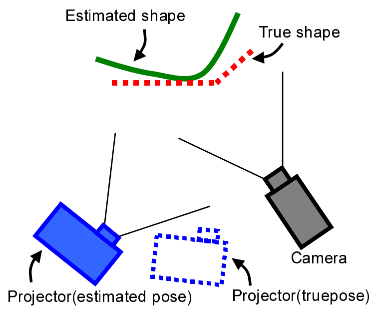


Figure 2. False shape reconstruction of a projector-camera system.

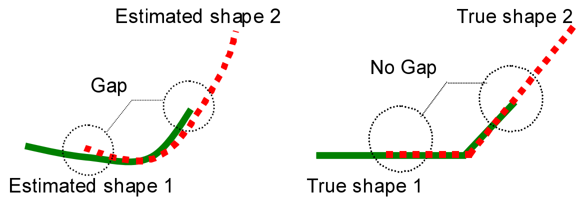


Figure 3. A gap of registration by a shape error: (left) registration of shapes with errors, and (right) registration of accurate shapes

2. Related works

Dense shape reconstruction using a camera is one of the most important topic for CV and currently there are many researches conducted to recover the entire shape of the object using multi-view geometry techniques [8, 15]. However, such methods basically require a precise calibration for all views and it is still a laborious task. On the other hand, SfM method, which does not require pre-calibration, but simultaneously estimates the shape and the positions of the moving camera, has been researched for a long time. SfM method usually estimates the initial values by utilizing a closed-form solution, such as factorization [16]. After that, the final camera parameters and motion parameters are refined by bundle adjustments [17] through non-linear optimization. However, SfM needs precise feature extraction, which is not easy especially when the target objects are textureless.

Because of the problems of SfM, such as difficulties in measuring textureless objects, and producing dense 3D shapes, active range sensors are usually used for actual 3D scanning. In order to measure a large scene or an entire shape of a target object, measurements are taken multiple times from different viewpoints, and the acquired shapes are integrated afterwards. A well-known algorithm used for registering the measured shapes from the multiple views is the ICP (Iterative Closest Point) algorithm [2, 6, 18, 13, 12]. Regarding shape data that has been registered to some extent, the ICP algorithm registers the shape precisely by repeatedly estimating the data's correspondence and the motion parameters based on that correspondence. However, even if these methods are applied, original distortion in the shape due to errors of the range sensors causes gaps in the

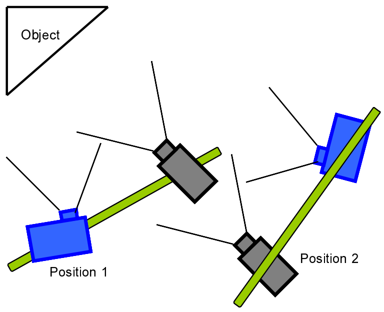


Figure 4. A projector-camera system for 3D acquisition.

integrated shape.

In terms of range sensors, among wide varieties of them [1], systems that use coded structured light with a projector-camera system [1, 5, 3, 10, 9] are widely used, because of its high precision, simple configuration and easy manipulation. Thus, we also adopt the system for our research. To scan an object accurately, precise calibration of a projector-camera system is necessary, because a precision of the reconstruction is directly influenced by calibration parameters. Therefore, in this paper, we estimate calibration parameters as well as motion parameters simultaneously to retrieve the better result.

3. Entire shape acquisition by multi-view active-stereo

3.1. Outline

The outline of the proposed algorithm is as follows. First, we perform multiple 3D shape reconstructions using an active stereo method with the projector-camera system. Since we do not assume pre-calibration step in the system, we estimate the initial extrinsic parameters using self-calibration [7] and subsequently acquire the initial shape (Sec. 3.2). Next, a rough registration is performed using feature tracking using images captured by cameras followed by a precise registration by ICP and these are used as the initial values of the motion parameters (Sec. 3.4). Since wrong correspondences sometimes occur using image feature, the motion parameters are refined by using the ICP algorithm to improve stability of the bundle adjustment. Finally, with regard to the overlapping areas of each shape, multiple 3D points are sampled, and those 3D points are used for bundle adjustment to optimize all the parameters (Sec. 4).

3.2. System and data capturing process

The system proposed in this paper consists of a projector and a camera that are relatively fixed in position by, for example, a rig as shown in Figure 4. It uses coded structured light method to measure 3D scenes. To capture a 3D shape of the scene, the projector and the camera are pointed at the target object, and images of the object are taken while multiple patterns are projected onto it. The correspondences for the projector-camera system can be obtained by decoding the captured patterns. By repeating this process while moving the projector-camera pair, multiple shapes from multiple views are acquired (Figure 1).

3.3. Parameters to be estimated

The parameters to be estimated with the proposed method include: (a) intrinsic parameters for the projector and the camera, (b) relative position and orientation for the projector-camera system, which are usually called extrinsic parameters, (c) motion parameters for each viewpoint, and (d) 3D coordinates for sampled points on the shape. With regard to (a), we assume that all of the initial values for the intrinsic parameters have some level of precision, and the only parameter estimated using the proposed method is the focal length. This is due to the fact that focus or zoom adjustments are often desired in real cases of measurements because of shallow field of depth of projectors.

3.4. Initial parameter estimation

Since we do not assume any explicit calibration process, all the initial parameters should be estimated without using a calibration pattern or box.

In terms of estimation of extrinsic parameter for a projector and a camera system, we can apply a self-calibration technique proposed by Kawasaki et al. [7]. The technique is a simple extension of a self-calibration technique of a stereo camera pair to a projector and a camera system. To retrieve correspondences between the projector and the camera, the system projects a number of patterns. Since a large number of correspondence can be retrieved by the projector-camera system, extrinsic parameters can be stably estimated. After estimation, dense 3D shapes can be reconstructed.

In terms of estimation of motion parameters between projector-camera system pairs, we can use images which are captured by a camera. Actual process is as follows:

1. Apply feature extraction and tracking algorithm between successive frames to acquire correspondences. For a feature extraction, SIFT [11] was used.

2. Estimate rigid transformation parameters by using 3D coordinates of correspondences as described in [2].

3. Apply ICP [2] to all the 3D points to achieve precise registration.

In actual process, it sometimes happened that correct motion parameters are not estimated because of failure in retrieving enough correspondences especially for textureless object, such as plaster figures in Step 1. At that time, we manually select correspondences to estimate rough motion parameters before Step 3.

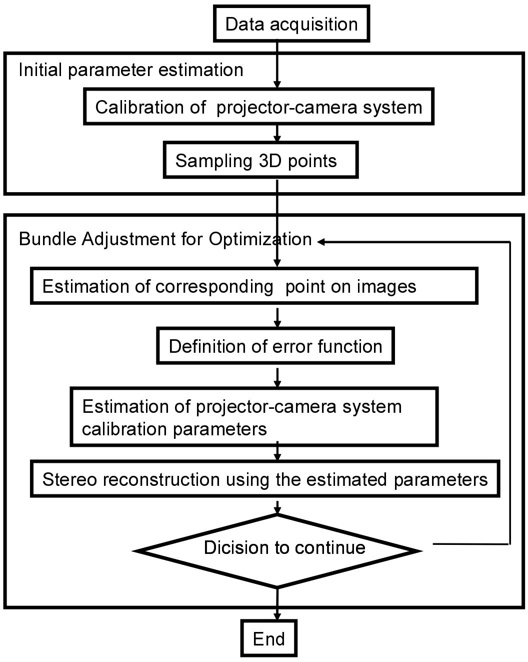


Figure 5. Flow of the process.

4. Bundle adjustment for projector camera systems

4.1. Outline

To optimize the parameters of the initial estimation, the bundle adjustment algorithm, which is normally used for multi-view stereo, is applied to a projector-camera system. The actual process is as follows. First, correspondences between 3D points of range images captured from different viewpoints are searched (Section 4.3). Each of the 3D points is associated with a pair of 2D points from a projector-camera pair from which the 3D position is calculated. Thus, correspondences between 3D points of different viewpoints determine a set of corresponding 2D points on the image planes of the projector and the camera with the viewpoints. Then, the calibration parameters of the projector-camera system and the 3D positions of the sample points are optimized simultaneously by minimizing the errors between the projection of estimated 3D points and the coordinates of the 2D points that are associated to it, using the same algorithm with a normal bundle adjustment (Section 4.4). The 3D shapes are reconstructed using the updated parameters, and using them, new correspondences are searched (Section 4.5). All the processes are repeated until changes of the parameters all become lower than fixed values.

4.2. Sampling of points for bundle adjustment

Because the bundle adjustment optimization is nonlinear, when the number of estimated parameters increases, the processing time greatly increases together with the instability. In order to prevent this, we sample points from the depth images to reduce the computational costs. In the current implementation of this study, random sampling from the valid pixels of the range images is used. This sampling process occurs only once, and the sampled points are fixed throughout all the subsequent processes. During the bundle adjustment process, sample points for which correspondences cannot be found are not used.

4.3. Acquisition of correspondence points

If the system consists of only cameras, the correspondence points are stably obtained by tracking feature points on the images. However, with projector-camera systems, correspondences between range images of different viewpoints cannot be acquired explicitly, which should be determined to use bundle adjustment. In the proposed method, the closest 3D points from a sample point searched from each of the other reconstructed range images of the different viewpoints are used as the corresponding points of the sample. Since this does not ensure correct correspondences, the corresponding points are updated iteratively. The details of the algorithm are as follows: (Please see Figure 6)

Step 1 One of the sampled points is selected. The points corresponding to the selected point on the shapes reconstructed from projector-camera pairs of different viewpoints are estimated using the nearest-neighbor search technique [13]. (Figure 6-(1) and (2))

Step 2 Each of the 3D points has corresponding 2D points on the image planes of the camera and the projector, from which it is reconstructed. Using this information, the correspondences between the 2D points on the image planes from different viewpoints can be estimated from the correspondences between the 3D points estimated in Step 1. (Figure 6-(3))

Step 3 Since the projector is an inverse camera and cannot obtain correspondences, they can be obtained by decoding the corresponding point on the image plane of the camera from the captured image sequence of a coded structured light. (Figure 6-(4))

Steps 1 to 3 are repeated for all the sample points to acquire the correspondences on the image planes.

4.4. Modified bundle adjustment for projector-camera systems

Next, the sampled 3D points are all projected onto the image planes of the projector and the camera, and the sum of the respective squared errors between the projected points and the corresponding 2D points is minimized (Figure 7). This process is a modified version of bundle adjustment; the modified point of the proposed method from the

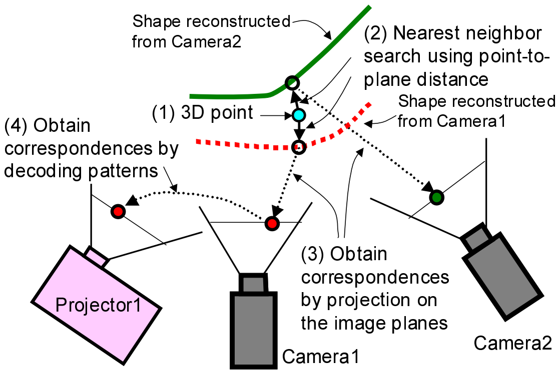


Figure 6. Estimation of corresponding point.

normal bundle adjustment is that the relative position between the projector and the camera is fixed, whereas all the positions of the projector and the camera can be free with each other for normal bundle adjustment. This constraint is a simple representation of the fixed relative relationship between the projector and the camera, and it helps to obtain stable results.

Let the estimated 3D point of the set of corresponding points obtained from the i-th sample point be represented as $\mathbf{P}_i$ in the object coordinates. Then, its projection on the image planes is expressed as a 2D vector

$$\mathbf{u}^C_{i,j}(\mathbf{x}) = \mathrm{Proj}^C_j(\mathbf{R}^C_j \mathbf{P}_i + \mathbf{t}^C_j), \tag{1}$$

where $\mathbf{R}^C_j$ and $\mathbf{t}^C_j$ are the rotation and the translation of the rigid transformation that converts the object coordinates into those of camera j, Proj^C_j is the projection of camera j and $\mathbf{x}$ is a vector that includes all the parameters to be estimated. In addition, vector $\mathbf{x}$ includes the intrinsic parameters of the camera and the projector (in the experiment they are the focal length of the camera and the focal length of the projector), the parameters that represent the rigid transformation from the object coordinates into the camera coordinates with the exception of camera 1 ($\mathbf{R}^C_2, \cdots, \mathbf{R}^C_K \mathbf{t}^C_2, \cdots, \mathbf{t}^C_K$), the relative position of the camera and the projector fixed for all the viewpoint ,i.e., extrinsic parameters $\mathbf{R}^E$ and $\mathbf{t}^E$, and the 3D locations of sample points ($\mathbf{P}_1, ..., \mathbf{P}_L$). K is the number of projector-camera pairs (i.e., number of viewpoints), and L is the number of sample points.

Because the selection of the target object coordinates is arbitrary, the conversion parameters $\mathbf{R}^C_1, \mathbf{t}^C_1$ for the target object coordinates and the coordinates for camera 1 are fixed.

Similarly, the point where $\mathbf{P}_i$ is projected onto projector j is

$$\mathbf{u}^P_{i,j}(\mathbf{x}) = \mathrm{Proj}^P_j(\mathbf{R}^E(\mathbf{R}^C_j \mathbf{P}_i + \mathbf{t}^C_j) + \mathbf{t}^E), \tag{2}$$

where Proj^P_j is projection of projector j.

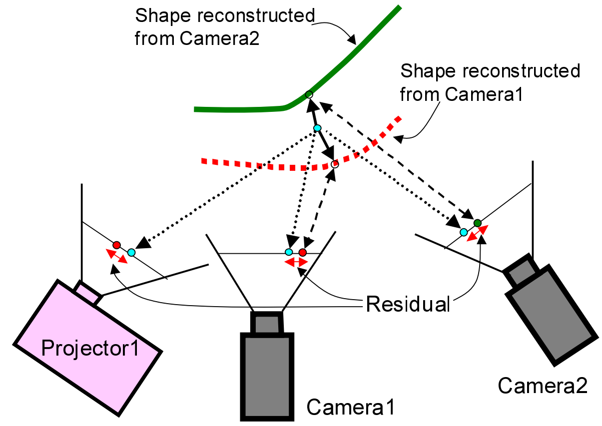


Figure 7. Residual error.

Based on the formulation, the error vector $\mathbf{f}_{i,j}(\mathbf{x})$ for point i and camera j, and the error function $E(\mathbf{x})$ are defined as follows:

$$\mathbf{f}_{i,j}(\mathbf{x}) := \begin{bmatrix} \mathbf{u}^C_{i,j}(\mathbf{x}) \\ \mathbf{u}^P_{i,j}(\mathbf{x}) \end{bmatrix} - \begin{bmatrix} \mathbf{v}^C_{i,j} \\ \mathbf{v}^P_{i,j} \end{bmatrix} \tag{3}$$

$$E(\mathbf{x}) := \sum_{i=1}^{L} \sum_{j=1}^{K} \|\mathbf{f}_{i,j}(\mathbf{x})\|^2 \tag{4}$$

where $\mathbf{v}^C_{i,j}$ and $\mathbf{v}^P_{i,j}$ are the coordinates on the screens that correspond to $\mathbf{u}^C_{i,j}(\mathbf{x})$ and $\mathbf{u}^P_{i,j}(\mathbf{x})$, respectively.

4.5. Dense Stereo Reconstruction

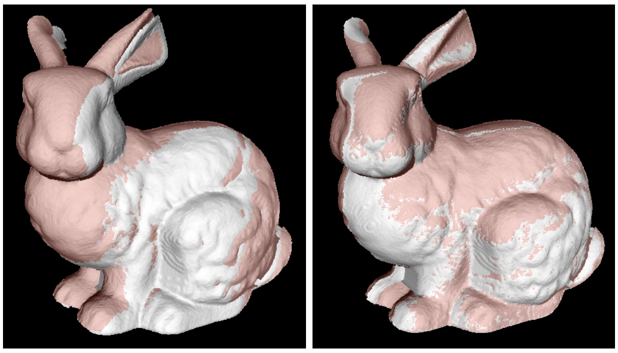
From the bundle adjustment process, motion parameters between different viewpoints and the extrinsic parameters between the projector and the camera are obtained. Therefore, we can use the extrinsic parameters to reconstruct dense 3D points by ordinary stereo method for all the viewpoints. Since the positional relationships between the projector and the camera are changed and the reconstructed shapes are modified, the correspondences between the 2D points on image planes of different viewpoints are changed, and thus, should be updated. We re-estimate the correspondences by the method described in section 4.3. The final solution is obtained by repeating the whole processes until a residual error stop decreasing.

5. Experiments

5.1. Evaluation using synthetic data

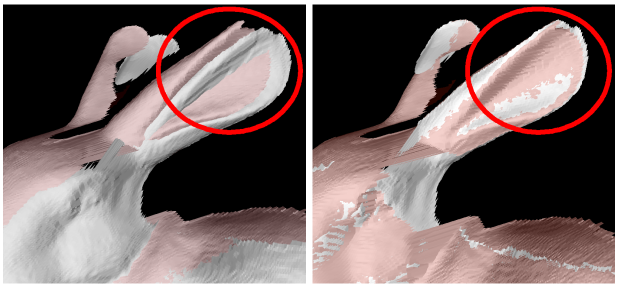
In order to verify the effects of the proposed method, we performed experiments using simulation data and actual data, and evaluated the proposed method.

First, we used a polygon model of a rabbit for the experiment. The extrinsic parameters for the projector-camera system were set to predetermined values, and the measurements and simulated input data were then synthesized. As



(a)Data with error (b)Shape after optimization

Figure 8. Simulation data result of optimization.



(a)Data with error (b)Shape after optimization

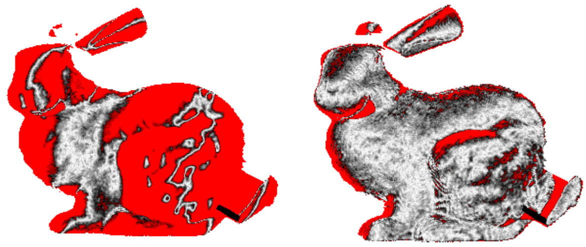
Figure 9. Simulation data result of optimization (closeup view).

for the resulting synthetic data, the initial values for the intrinsic parameters were set as the focal length parameters of the camera by applying a 10% error. The extrinsic parameters of the projector-camera system were unknown. Bundle adjustment was then performed using the proposed method. Accordingly, the initial values of the extrinsic parameters were estimated using self-calibration. The shapes reconstructed with these parameters as well as the results registered using the ICP algorithm are shown in Figure 8 (a) and 9 (a). We can see that the shape was distorted due to the 10% error applied to the focal length, and could not be registered correctly.

The results of applying the proposed method to this data are shown in Table 1, and in Figure 8 (b) and 9 (b). Because the values comprise simulation data and have no unit as a reference, the distance from the camera to the center of gravity of the target object was calculated, and it was 0.076. We can see that by using the proposed method, the residual error in the shape has been reduced. Figure 10 shows a visualization of the error in the shape, where the darker the shading, the larger the error is. Areas with especially large error are colored in red. The threshold value for the coloring to turn red is 0.0025. From this figure, we can see that the error in the shape was reduced.

5.2. Experiment using real object (Plastic toy)

Next, an experiment was performed using data measured from 11 directions of the target object (plastic toy),



(a) Before optimization (b) After optimization

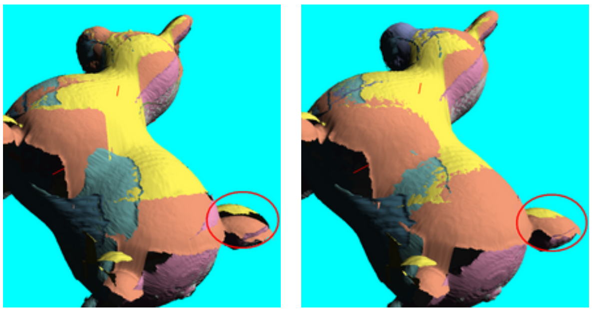
Figure 10. Registration errors of simulation data.

Table 1. Residual errors between shapes of simulation data.

	Mean error
Before optimization	3.45×10^{-1}
After optimization	0.11×10^{-1}

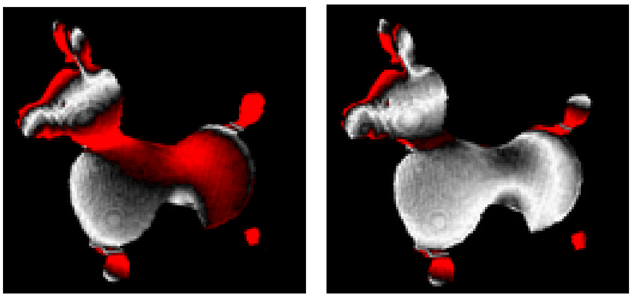
Figure 11. (Left) the target scene and (right) initial shape.

as shown in Figure 11 (left). Multiple measurements were taken while moving the projector-camera pair. We tested reconstruction using the proposed method without performing any preliminary calibration except intrinsic parameter calibration. Therefore, the initial values of the extrinsic parameters between projector and camera were estimated using self-calibration. The shape obtained from the measurements is shown in Figure 11 (right). As we can see in Figure 12(a), before bundle adjustment was performed, the estimation errors in the extrinsic and intrinsic parameters prevented multiple shapes from being registered correctly. The results of using the proposed method with this data are shown in Table 2. Also, with regard to post-parameter correction using the proposed method, Figure 12(b) shows a magnified image of the overlapping sections of the shape. We can see that the application of the proposed method has reduced the deviation during registration. Figure 13 shows a visualization of the error in the shape, where the darker the shading, the larger the error. Areas with especially large error are colored in red. The threshold value for the coloring to turn red is 0.04m. From this figure, we can see that the error in the shape was reduced, and the distortion was removed.



(a)Before optimization (a)After optimization

Figure 12. Registration result of real data (plastic toy with closeup view).



(a) Before optimization (b) After optimization

Figure 13. Registration error of real data (plastic toy).

Table 2. Residual errors between shapes of real data (Unit of figures is m^2).

	Mean error
Before optimization	2.62×10^{-3}
After optimization	1.24×10^{-3}

5.3. Experiment using wide scene (Room with sofa)

Next, an experiment was performed using data measured from three directions of a complex scene that included multiple objects (a sofa, a sled, and a Styrofoam cylinder) as shown in 14 (left). The active stereo method based on pattern coding was used for the measurements. A fixed projector-camera set was used; thus, the relative position of the projector and the camera does not change. Multiple measurements were conducted while moving the fixed projector-camera pair. The baseline between the projector and camera was approximately 30 cm. The extrinsic parameters of the projector-camera system were estimated in advance using a calibration box to be 20 cm $\times$ 20 cm $\times$ 20 cm, and these were set as the initial values. Also, in order to measure the complex scenes in this experiment, measurements were taken while the focal length of the projector-camera system was changed. The image used for calibration, which was captured by the actual projector-camera system used to take the measurements, is shown in Figure 14 (right). Since the calibration object was small relative to the size of the room, the image of the object in a captured image was also small. Therefore, the precision of the initial values of the estimated extrinsic parameters was not enough accurate for registration. The shape obtained from the measurements is shown in Figure 15, where (a) is a texture-mapped example in the case when all of the shapes are registered, and (b) shows the shading for each shape by color. We can see that the shapes from each view are distorted due to the low precision of the intrinsic and extrinsic parameters of the projector-camera system, which prevents the registration from being performed correctly. The results of using the proposed method with this data are shown in Table 3 and Figure 16. When first registered by ICP, there was deviation in the shape caused by the errors in the intrinsic and extrinsic parameter areas. The proposed method succeeded in reducing the deviation in the shape and was able to successfully perform registration without deviation. Figure 17 shows a visualization of the error in the shape, where the darker the shading, the larger the error. Areas with especially high error are colored in red. The threshold value for the coloring to turn red is 0.02(m). We can see that the error in the shape in each figure was reduced and the distortion was removed.

Figure 14. Real data: (left) the target scene and (right) calibration box.

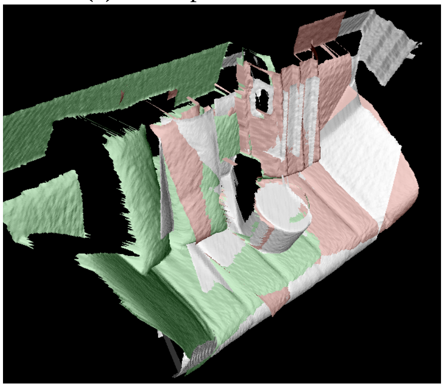
Table 3. Residual errors between shapes of real data (Unit of figures is m^2).

	Mean error
before optimization	3.22×10^{-4}
after optimization	1.99×10^{-4}

6. Conclusion

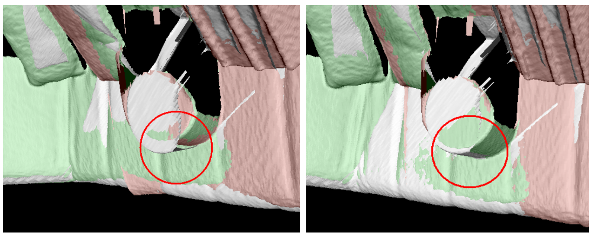
The method proposed in this paper applied the multi-view reconstruction approach for a camera system to a projector-camera system. This resulted in increased precision of the intrinsic and extrinsic parameters as well as the motion parameters for different viewpoints for the projector-camera system. Thus, the proposed method allows the reconstruction of wide scenes and the entire shape of the objects with high accuracy. Future work should examine the acquisition of correspondences with high precision using shape features and the improvement of processing speed.

(a)All shapes with texture



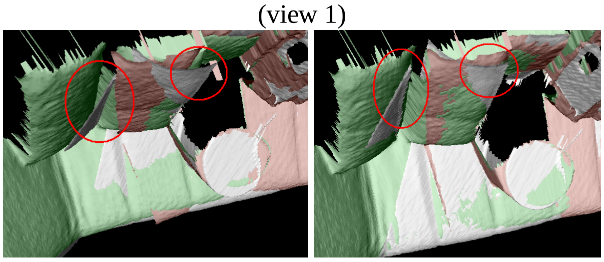
(b)All shapes with shading

Figure 15. Acquired 3D data of complex scenes.



(a)Before optimization (a)After optimization

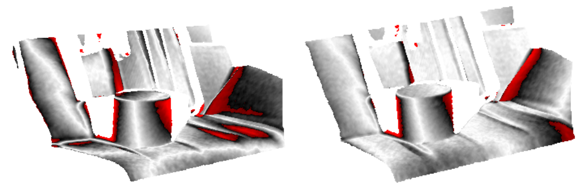
(view 1)



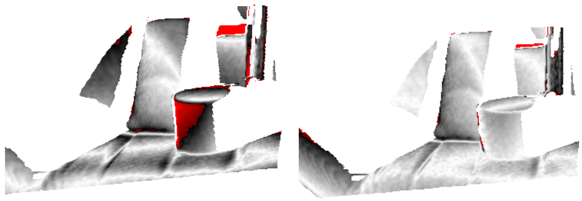
(c)Before optimization (d)After optimization

(view 2)

Figure 16. Registration result (complex scenes with closeup view).



(a) Before optimization (b) After optimization



(a) Before optimization (b) After optimization

Figure 17. Registration error (complex scenes).

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