System Identification: 3D Measurement Using Structured Light System

Deokwoo Lee and Hamid Krim

Department of Electrical and Computer Engineering
North Carolina State University
Raleigh NC 27606, USA
{dlee4,ahk}@ncsu.edu
http://www.vissta.ncsu.edu/

Abstract. The problem of 3D reconstruction from 2D captured images is solved using a set of cocentric circular light patterns. Once the number of light sources and cameras, their location and the orientations, and the sampling density (the number of circular patterns) are determined, we propose a novel approach to representation of the reconstruction problem as system identification. Akin to system identification using the relationship between input and output, to develop an efficient 3D functional camera system, we identify the reconstruction system by choosing / defining input and output signals appropriately. One algorithm states that an input and an output are defined as projected circular patterns and 2D captured image (overlaid with deformed circular patterns) respectively. Another one is that a 3D target and the captured 2D image are defined as the input and the output respectively, leading to a problem of input estimation by demodulating an output (received) signal. The former approach identifies the system from the ratio of output to input, and is akin to a modulation-demodulation theory, the latter identifies the reconstruction system by estimating the input signal. This paper proposes the approach to identification of reconstruction system, and also substantiates the algorithm by showing results using inexpensive and simple experimental setup.

Keywords: 3D reconstruction, Structured light system, Circular patterns, System identification, Ratio of the output to input, Modulation-demodulation theory.

1 Introduction

Structured light systems have been extensively used to efficiently measure 3D object information (e.g. geometric / photometric information) from 2D observed scenes (e.g. captured image in a camera) ([8], [9], [10]). Jason Geng [11] has reviewed the previous 3D reconstruction algorithms using the deformation of light patterns, phase differences of projected light patterns or codes (e.g. binary, color, etc.) assigned to the patterns. Deokwoo Lee [1] has proposed a simple and efficient reconstruction algorithm using circular light patterns. By establishing a

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relationship between the original circular patterns and the deformed ones due to the surface shape, 3D real world coordinates are recovered. To achieve high quality reconstruction results, we can increase the sampling density (i.e. increase the number of circular patterns to be projected onto the target object.), but the higher reconstruction accuracy may result in complex and high-cost reconstruction system. Akin to sampling rate determination based on the *Shannon-Nyquist Sampling Theorem* [12], maximal spatial frequency component is estimated using specific geometric information (e.g. the highest curvature). The optimal sampling rate, *the minimum number of circular patterns*, for a reconstruction, is determined by the maximum spatial frequency component [13]. In the areas of object recognition or of classification, extremely accurate reconstruction may be inefficient, therefore, approximate reconstruction is sufficient to uniquely characterize the target object and this leads to employing a concept of *system identification.* In the field of system identification, the system is uniquely represented by the interrelationship of the input and the output signal(s) (Fig. 1). The system can be determined efficiently by appropriately selecting input signals, for instance, a *dirac delta function*, a *step function*, a *pseudorandom binary sequence*, a *sinusoidal function*, etc. These are widely used input signals for system representation [14]. The reconstruction problem can be considered a *system identification problem.* Since it is very difficult and inefficient to recover entire 3D object information, efficient 3D reconstruction (approximate reconstruction) may be achieved by simply characterizing the target object, such that recognition or classification is possible. One of the most widely used methods for characterizing a system is representing it using the ratio of output to input. For example, *Fourier transform*, *Laplace Transform* or *Z-transform* enables us to represent a system as the ratio of output to input. In the reconstruction work using circular patterns, to employ the concept of *system identification*, the 3D object is defined as the system, and we need to select an appropriate input signal rather than the ideal signals shown above. Therefore, this paper defines the system as the 3D object, and the reconstruction problem is then restated as the system identification problem. The reconstructed object can be represented as the ratio of output to input, where the output includes the information of deformed patterns and the input includes the information of the original patterns. Instead of using ideal input signals, a single circular pattern is projected and the deformed pattern is captured in a 2D image plane. This paper establishes the ratio of the output to input in object space domain, and the characteristics of the object are represented based on the *Thales Theorem* [6].

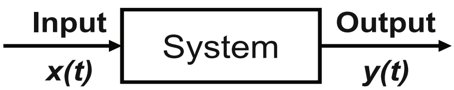

Fig. 1. A system (generally, static or dynamic) with input $x(t)$ and output $y(t)$ is defined as the ratio of the output to input in frequency, Laplace or Z domain

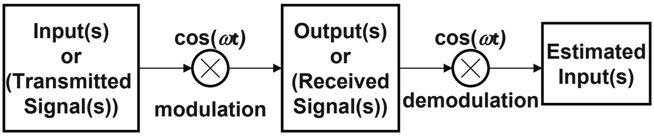

Fig. 2. In communication system, the *modulation-demodulation theory* is used to detect the user(s) or transmitted signals from the output signal(s) using carrier signal, $\cos \omega t$

Another method to achieve an efficient reconstruction system is employing communication systems. In communication systems, modulation-demodulation theory [7] is used to detect / estimate a transmitted signal (input signal). Carrier frequency is used for modulation and demodulation processes (Fig. 2). The *modulation-demodulation theory* can be applied to the reconstruction system by defining the input and output signal as the 3D object which is to be reconstructed and the observed scene in a 2D image plane, respectively. Although we do not actually use the carrier signal, in the reconstruction system, circular patterns play the role of a carrier signal (Section 3.2). This paper provides method to represent 3D reconstruction results, especially in a multiple-projector(input)-viewpoints(output) system, using a modulation-demodulation theory, called *MIMO-MODEM reconstruction.* There have been no contributions relating the reconstruction problem to system identification, by representing the reconstruction system using a *the ratio of output to input* or a *modulation-demodulation theory*, and we can achieve a very efficient reconstruction system leading to the development of an efficient and low-cost 3D functional camera. In addition the proposed approaches can be applied to many areas of 3D imaging.

The organization of the rest of the paper is as follows : The next section will briefly explains a geometric 3D reconstruction algorithm which is designed on the basis of structured circular light patterns. Section 3 is the most important contribution of this paper, where the reconstruction problem is represented as the *system identification* problem ; *the ratio of output to input* and a *modulation-demodulation theory.* Using a *system identification*, the ratio of the output to input in a space domain represents the *system function* of the reconstruction work, and the output and input correspond to the characteristics of the deformed and the original circular patterns, respectively (Section 3.1). *Modulation-demodulation theory* is employed to represent the reconstruction problem by estimating input signal(s) (the target object(s)) (Section 3.2). We substantiate the proposed algorithms in Section 4 prior to the conclusion.

2 Geometric 3D Recovery Algorithm

The problem of 3D reconstruction from 2D captured images is solved using a set of cocentric circular patterns each of which has a different radius. Without any prior information about a target, the reconstruction problem can be solved by the active method. The patterns projected onto the object surface are deformed due

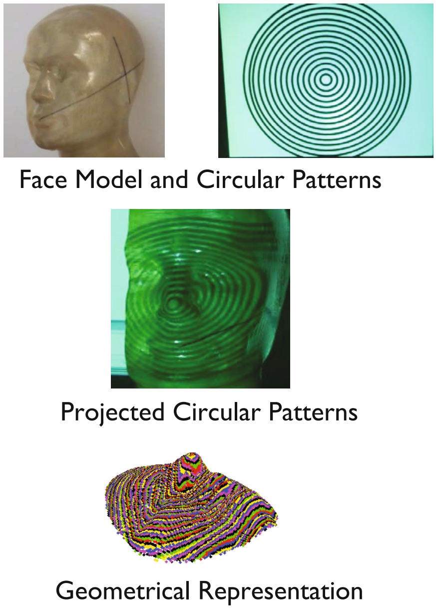

Fig. 3. A face model is illuminated by a set of cocentric circular patterns. Given the information of the original circular patterns, deformed circular patterns provides sufficient information to recover 3D real world coordinates of the face model.

to its shape. Comparison between the original circular patterns and the deformed ones provides sufficient information to recover complete 3D coordinates of the target (Fig 3). The structure of circular patterns (i.e. radii and the location of the center of circles, and the location of the light source are known), the location of the arbitrary reference plane and optical center of the camera are also known as assumed in Deokwoo's work [1]. Although the calibration of a camera and projector is also an independent research topic in 3D imaging, this paper is focused on the geometric reconstruction algorithm ([2], [3], [4]). In [1], mathematical modeling and simulation results are presented, and this paper uses the principle of the reconstruction algorithm using circular patterns to represent the reconstruction algorithm as a system identification.

3 System Identification

This section details the approaches to representing the reconstruction problem using a *system identification*. In general, a system is composed of input and output. The reconstruction problem is restated as the relationship between input and output signals in Section 3.1. Alternatively, the reconstruction problem may be restated as an input estimation problem. In communication systems, the transmitted signal is estimated using a *carrier signal* when we use a *modulation-demodulation theory*. The object to be reconstructed is considered an estimated input and the *carrier signal* is considered a set circular patterns each of which has a different radius. To avoid confusion, the input, output and system are denoted by $A(t)$, $B(t)$ and $H(t)$, respectively, and t, the position of a circular pattern, is sometimes omitted.

3.1 The Ratio of Output to Input

Let us define A, H and B as an inputs, system and output respectively. In the reconstruction problem, the target object ($H \subset \mathbb{R}^3$) is projected on a set of circular patterns ($A \subset \mathbb{R}^3$). The observed scene ($B \subset \mathbb{R}^2$) is in a 2D image plane, and is an object overlaid with circular patterns. In general, a very well known method to identify a system is by estimating or measuring an output signal as a response to *dirac delta function* as an input signal. In our image reconstruction problem, since generating such an input signal is not possible in practice, we use a single circular pattern to identify a system (i.e. a target object). Our goal in this section is to acquire a system function, H, using A and B. Let $M \subset \mathbb{R}^3$ and $m \subset \mathbb{R}^2$ be real points of an object and imaged points, respectively. According to the *Thales' Theorem* [6], the relationship between M and m is the following (or see Fig. 4):

$$x = z\frac{u}{f},\ y = z\frac{v}{f}, \tag{1}$$

$$x^2 + y^2 = R^2, \tag{2}$$

$$z = \frac{fR}{\sqrt{u^2 + v^2}}, \tag{3}$$

where f is the *focal length* of a camera, and R is a radius of a circular pattern, respectively (See Fig.4). The depth value, z characterizes the target object because it deforms the projected circular patterns, and we define the *system function* as *the ratio of the output to input*,

$$H(t) = \frac{B(t)}{A(t)}, \tag{4}$$

$$A(t) = \frac{1}{f(t)R(t)}, \tag{5}$$

$$B(t) = \frac{1}{\sqrt{u(t)^2 + v(t)^2}}, \tag{6}$$

where the domain of input and output is defined as the positions of projected curves (Fig. 5) and the *focal length* is assumed to be invariant (i.e. $f(t) = f$). Alternatively, the ratio of neighboring depths can be considered a system function (i.e. $H(t) = \frac{z(t)}{z(t+1)}$). Another approach to the system identification is the ratio of a curve velocity. The velocity of a curve ($\alpha(t) = (x(t), y(t))$) is $\sqrt{x'(t)^2 + y'(t)^2}$, and let V_I and V_O be a velocity of an original circle and a deformed circle, respectively. The system function $H = \frac{V_O}{V_I}$ is represented as

$$V_I = \sqrt{x_I'(t)^2 + y_I'(t)^2} = R(t)\omega(t), \tag{7}$$

$$V_O = \sqrt{x_O^{'}(t)^2 + y_O^{'}(t)^2} = \sqrt{\left(\frac{dr(t)}{dt}\right)^2 + \theta'(t)^2 r^2(t)}, \tag{8}$$

$$x_I^{'}(t) = \frac{dx_I(t)}{dt}, \; y_I^{'}(t) = \frac{dy_I(t)}{dt},$$

$$x_O^{'}(t) = \frac{dx_O(t)}{dt}, \; y_O^{'}(t) = \frac{dy_O(t)}{dt},$$

$$H = \frac{V_O}{V_I}, \tag{9}$$

where $\theta(t) = \arctan(y_O^{'}(t)/x_O^{'}(t))$, $\alpha_I(t) = (x_I(t), y_I(t))$ and $\alpha_O(t) = (x_O(t), y_O(t))$ represent the original circular patterns and the deformed patterns, respectively, and $\omega(t)$ is an angular frequency. Using a *Fourier Descriptor* [5], we

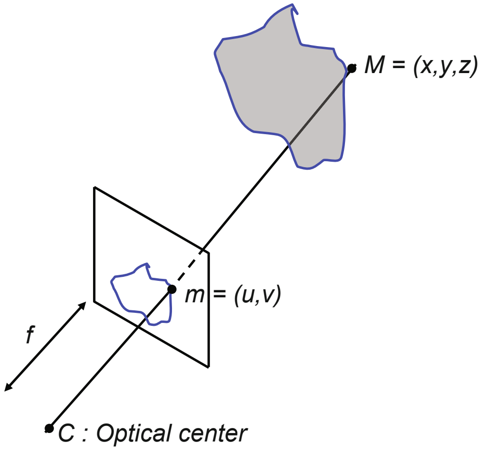

Fig. 4. According to *Thales' Theorem*, and using circular patterns, the relationship between 3D and 2D points is established

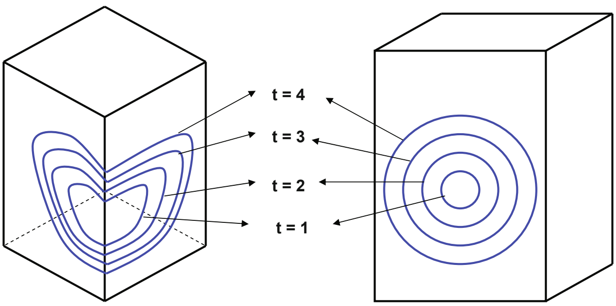

Fig. 5. Instead of *Fourier, Laplace* or *Z domain*, our system is defined in the domain of the position of a circular pattern

also can obtain a ratio of fourier coefficients of original and deformed circles to identify a system. The system function may be acquired using intensity values of illuminated light patterns on an object. Assuming that the distance between an arbitrary reference plane of an object and a light source is invariant, the light intensity of illuminated light patterns on the object depends only on the depth of the object (by *the Inverse-Square Law*) [15]. This idea leads to the reconstruction system using a shape from shading algorithm ([16]).

3.2 MIMO MODEM Theoretic Algorithm

This section formulates the reconstruction problem using concepts of the *multiple input-multiple output* communication system and *modulation-demodulation* theory. In communication systems, once signals are transmitted with a carrier signal, called *modulation*, transmitted signals are estimated / detected by demodulating received signals (*demodulation*) (Fig. 2). When the signal is transmitted and reconstructed, a *Nyquist Sampling Rate* is used. A low-pass filter is used to complete the transmitted signal estimation and the cutoff frequency is determined by the bandwidth of the transmitted signal. Akin to the principle of modulation and demodulation, our reconstruction problem may be stated using the same system notions. The transmitted signals and the received ones correspond to the target object(s) and the captured image(s) of the object(s) overlaid with projected circular light patterns. Once the transmitted and received signals are defined, we need to define the *carrier frequency component* to complete a reconstruction system (we call this a *MODEM reconstruction system*). Since the target(s) are overlaid with the projected circular patterns, and the solution of the depth recovery problem is closely related to the radius of the pattern (Eq. (3)), the *carrier frequency component* may associated to the radius of the pattern. Let $\mathbf{A} = [A_1, A_2, ..., A_N]$ be a set of target objects (or a single object composed of N subsets, A_1, A_2, ..., A_N), and $\mathbf{B} = [B_1, B_2, ..., B_N]$ be a set of observed scenes, using the previously derived reconstruction algorithm, the carrier frequency for a demodulation corresponds to $\frac{1}{f\mathbf{R}}$, where $\mathbf{R} = [R_1, R_2, ..., R_N]$ is a set of radii of circular patterns. Modulation process corresponds to projecting a circular pattern whose radius is $\mathbf{R}$. Note that $f\mathbf{R}$ is defined as the carrier frequency component of a reconstruction system (Fig. 6). Let $\mathbf{A}' = [A'_1, A'_2, ..., A'_N]$ be the estimated / detected transmitted signal(s), we can then write,

$$\mathbf{B} = \mathbf{A} \otimes_{mod} f\mathbf{R}, \tag{10}$$

$$\mathbf{A}' = \mathbf{B} \otimes_{demod} f\mathbf{R}, \tag{11}$$

where $\otimes_{mod}$ and $\otimes_{demod}$ are our modulation and demodulation operation, using a projection of circular patterns with radii R_i, and f is the *focal length* of a camera (assumed to be invariant). In Fig. 6, Obj_i is the input signal which is to be reconstructed, and the input is illuminated by a circular pattern. Projection of light patterns is referred to as *circular modulation*. Modulated input signals are represented as (u_i, v_i), captured image points in a 2D image plane. Using

Eq. 3, the depth of the object is recovered (to avoid confusion, $\otimes_{demod}$ is referred to as a *circular demodulation*). Akin to determining the sampling rate based on the *Shannon-Nyquist Sampling Theorem*, Deokwoo [13] presented an algorithm for a sampling rate determination to recover a surface coordinates, which is the minimum number of circular patterns (i.e. the minimum number of components $[R_1, R_2, ..., R_N]$). The reconstruction problem using circular light patterns with an arbitrary sized object or any number of objects may hence be restated as a multiple input-multiple output(MIMO) theoretic problem with an associated solution.

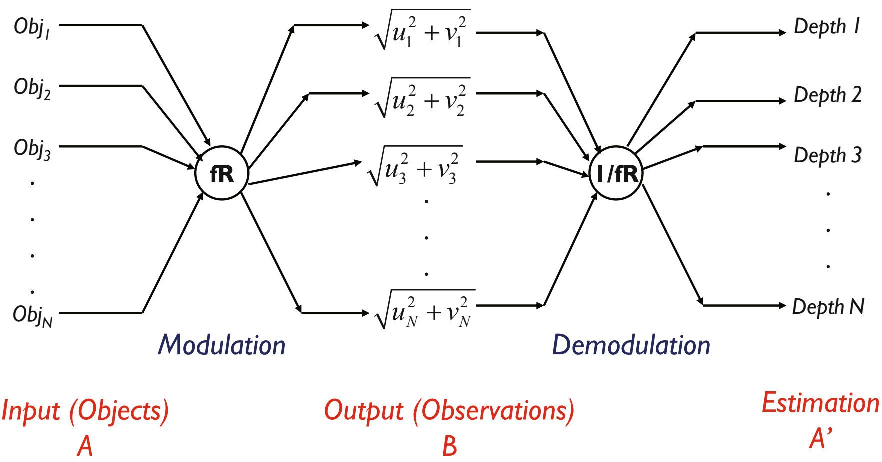

Fig. 6. Radius of a projected circular pattern is used to estimate the depth of an object and the reconstruction system can be represented using a communication system

4 Experimental Results

This section substantiates the proposed algorithm using simple experimental setup. To acquire clear projected light patterns on the object, we used a projector, but from a practical perspective, low-cost LED light source and a light modulator may be used instead of a projector. The experimental system includes projectors, cameras and a generic 3D object. A single-projector-viewpoint (SPV) and Multiple-projector-viewpoints (MPV) system requires a single projector and a camera (Fig. 7), and two or more projectors and cameras (Fig.s 8 and 9). Each projector, connected to a laptop computer, generates circular patterns, and is located approximately 1 meter away from the object. Regular (simple commercial digital) cameras fixed on tripods are used to capture the object overlaid with the projected circular patterns. These are also located approximately 1 meter away from the object. We used the following projectors and cameras ; 1024 × 768 resolution COMPAQ MP1600, 1024 × 768 resolution LCD EPSON POWERLITE 76C, and 1280 × 720 pixel resolution Canon camera [17]. The camera calibration

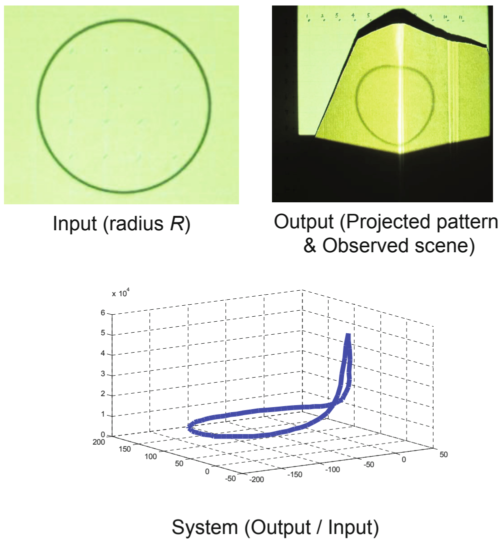

Fig. 7. Reconstruction of a terrain model Input : A, Output : B and System : $H = B/A$

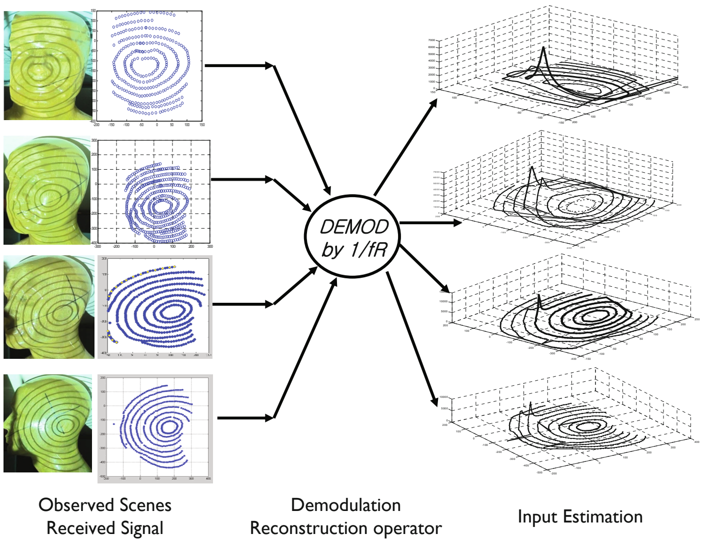

Fig. 8. The observed scene is composed of the target object overlaid with circular patterns. Akin to demodulation of communication system for estimating transmitted signals, the input, 3D object from each viewpoint, is estimated using projected circular patterns.

is performed using a checkerboard to estimate internal characteristics such as the *focal length*, an *image center*, etc. Estimated *focal length* is approximately 2480.3 pixels and an *image center*, (u_o, v_o), is $(792, 547)$. In reconstruction work, since we intend to measure relative 3D coordinates from the arbitrary reference plane, we deal with a scaling factor only tangentially. These parameters constitute a *projection matrix* [6]. The experimental results using the proposed algorithm in Section 3.1 and 3.2 are implemented in Fig.s 7, and 9, respectively.

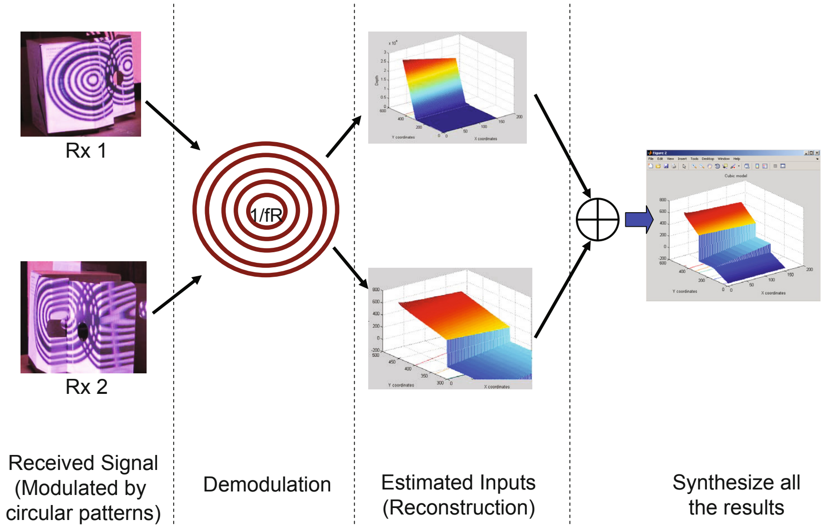

Fig. 9. The observed scene is composed of the target object overlaid with circular patterns. Once each observed scene is demodulated by the same circular patterns, 3D coordinates of the target is achieved.

5 Conclusion

In this paper, we have proposed a novel approach to reconstruction system identification. There were two approaches for system identification, one uses *the ratio of output to input*, and the other *the modulation - demodulation theory*. The former defines the input, the output and the system as a circular pattern (single or multiple patterns if needed), reconstructed 3D coordinates (i.e. depth), and the captured image of deformed patterns, respectively. By establishing the relationship between the parameters of the original and deformed circular patterns, the *system function* is determined in the spatial domain. The latter defines the input and the output as the target object and captured image, respectively. The input, the target, is estimated using a modulation-demodulation theory and this algorithm can be successfully applied to the case of multiple target objects (MIMO theoretic algorithm). Since this paper has presented novel approaches for 3D reconstruction systems related to the *system identification*, there is much future work to improve the proposed algorithm as well as to apply to other research areas, especially in vision, 3D imaging, etc. 3D reconstruction using structured light systems, requires accurate experimental setup for high quality reconstruction results. From a practical perspective, an experimental setup, such as camera calibration, preprocessing of object data to capture accurate 2D data points and a processing of noise effect (e.g. ambient light, specular component of an object, etc) should be carefully handled in future work.

References

1. Lee, D., Krim, H.: 3D Surface Reconstruction Using Structured Circular Light Patterns. In: Blanc-Talon, J., Bone, D., Philips, W., Popescu, D., Scheunders, P. (eds.) ACIVS 2010, Part I. LNCS, vol. 6474, pp. 279–289. Springer, Heidelberg (2010)
2. Hor, M.-K., Tang, C.-Y., Wu, Y.-L., Chan, K.-H., Tsai, J.-J.: Robust refinement methods for camera calibration and 3D reconstruction from multiple images. Pattern Recognition Letters 32(8), 1210–1221 (2011)
3. Li, T., Hu, F., Geng, Z.: Geometric Calibration of a Camera-Projector 3D Imaging System. In: Proceedings of the 10th International Conference on Virtual Reality Continuum and Its Applications in Industry, VRCAI 2011, pp. 187–194 (2011)
4. Wong, K.-Y.K., Zhang, G., Chen, Z.: A Stratified Approach for Camera Calibration Using Spheres. IEEE Transactions on Image Processing 20(2), 305–316 (2011)
5. Zahn, C.T., Roskies, R.Z.: Fourier Descriptors for Plane Closed Curves. IEEE Transactions on Computers C-21(3), 269–281 (1972)
6. Faugeras, O., Luong, Q.-T.: The Geometry of Multiple Images. The MIT Press Cambridge, Massachusetts
7. Proakis, J.G.: Digital Communications, 4th edn. McGraw Hill
8. Bruno, F., Bianco, G., Muzzupappa, M., Barone, S., Razionale, A.V.: Experimentation of structured light and stereo vision for underwater 3D reconstruction. Journal of Photogrammetry and Remote Sensing 66, 508–518 (2011)
9. Salvi, J., Batlle, J., Mouaddib, E.: A robust-coded pattern projection for dynamic 3D scene measurement. Pattern Recognition Letters 19(11), 1055–1065 (1998)
10. Fang, Y.-H., Chou, H.-L., Chen, Z.: 3D shape recovery of complex objects from multiple silhouette images. Pattern Recognition Letters 24(9-10), 1279–1293 (2003)
11. Geng, J.: Structured-light 3D surface imaging: a tutorial. Advances in Optics and Photonics 3(2), 128–160 (2011)
12. Papoulis, A.: Signal Analysis. McGraw-Hill (1977)
13. Lee, D., Krim, H.: A Sampling Theorem for a 2D Surface. In: Bruckstein, A.M., ter Haar Romeny, B.M., Bronstein, A.M., Bronstein, M.M. (eds.) SSVM 2011. LNCS, vol. 6667, pp. 556–567. Springer, Heidelberg (2012)
14. Söderström, T., Stoica, P.: System Identification. Prentice Hall (1989)
15. Iwahori, Y., Sugie, H., Ishii, N.: Reconstructing shape from shading images under point light source illumination. In: 10th International Conference on Pattern Recognition (1990)
16. Zhang, R., Tsai, P.-S., Cryer, J.E., Shah, M.: Shape-from-shading: a survey. Pattern Analysis and Machine Intelligence. IEEE Transactions on Pattern Analysis and Machine Intelligence 21(8), 690–706
17. Lee, D., Krim, H.: Surface Reconstruction: Multiple-View-Projector System. In: International Conference on Image Processing (submitted, 2012)