# 3D Shape Reconstruction using Single Camera and Two Mirrors 

Narayan Murmu ${ }^{1}$ and Debashis Nandi ${ }^{2}$<br>${ }^{1}$ Department of CSE, NIT, Durgapur, India<br>${ }^{2}$ Department of CSE, NIT, Durgapur, India

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#### Abstract

This paper presents a novel approach to 3D shape reconstruction of objects using a single camera-based stereo vision system. The system is based on two convex mirrors attached and aligned properly in front of a low-cost camera. The camera captures the stereo images of a scene formed in the two mirrors, and the 3D shape of any object present in the scene is reconstructed. The 3D reconstruction is performed by extracting the target object from the stereo images and applying a proper 3D reconstruction model. In the present work, the 3D reconstruction of a target object has been performed by computing disparity map and using 3D point clouding technique. The depth of each point of the objects and the disparity is determined using featured-based algorithm. The depth image, which sometimes is called point clouds or grayscale image, has been used to generate the 3D shape and position of an object. This new system adds the advantages of using the principle of stereo vision for 3D reconstruction and reduces the shortcomings of using a pair of cameras in the conventional stereo vision systems. The performance of the system is verified by identifying different objects of different shapes and sizes and reconstructed 3D outputs from captured stereo images.


Keywords: 3D Reconstruction, Stereo vision, Convex mirrors, Stereo matching

## 1. INTRODUCTION

Three-dimensional shape reconstruction of objects of a captured scene is essential in different computer applications like medical diagnosis, surveillance, robotic vision, radar imaging, etc. The 3D shape is beneficial for the visual navigation of robots, Geographic Information Systems (GIS), virtual reality, object modeling, collision avoidance, clinical diagnosis, and many other modern applications. A large area of applications has made it an active area of research in computer vision and graphics. Till date, many systems and algorithms have been developed for the reconstruction of the 3D shape of objects[1], [2], [3], [4], [5], [6], [7] The systems are mainly based on tomographic reconstruction, 3D scanning, and stereo imaging principles. Stereo vision-based 3D reconstruction systems have become popular for the following reasons: (1) They have the advantage of mimicking human vision systems; (2) 3D reconstruction of an object from stereo images is relatively more straightforward, which can be done by computing disparity map. (3) They can provide desirable accuracy; (4) System structure is simple, and (5) lesser expensive with respect to other 3D reconstruction systems. These advantages led scientists and engineers to develop many stereo imaging-based 3D reconstruction systems in recent years [8], [9], [3]. However, two camera based stereo vision systems suffer from the following shortcomings:

- They use a pair of cameras, which need the same zoom level and focal length. Hence, the system's calibration becomes an important task when it is required to replace any one of the two cameras.
- Another stringent requirement is the proper synchronization between the cameras. The system should capture the stereo images of a scene simultaneously. Even a slight loss of synchronization between the cameras may introduce a large amount of error in the computation of the disparity map, which may introduce a significant error in the reconstruction of the 3D object. Hence, the requirement of synchronization needs the additional electronic circuits, which increases the system's complexity and cost.
- For a constructing disparity map with sufficient accuracy, the two must have the same image quality in terms of contrast, resolution, etc. Even a small variation of these parameters in the two images may increase the complexity of the disparity map computation. Based on the above observations, we are motivated to develop a system that can reconstruct the 3D shape of the target objects in the captured stereo images. The proposed approach is very simple and consists of a camera with two multi-radius convex
mirrors installed and aligned correctly in front of the mirror. The two mirrors can form two virtual images, which can be treated as a scene in front of the camera. The camera will capture these virtual images.

3D reconstruction of an object is performed by utilizing these images. The detailed description of the proposed system and the principle of 3D reconstruction is illustrated in subsequent sections. This new system adds the advantages of using stereo vision for 3D reconstruction and reduces the shortcomings of using a pair of cameras in conventional stereo vision systems.

The proposed system can be used for robotic movement where 3D reconstruction of the surrounding directly affect the accuracy of the robot movement, and this 3D imaging system is able to acquire depth information of the scene. 3D visualization is another application where proposed system provides not only the 3D shape and color of target objects but also the geometric information like the distance, the area, the volume, etc.

The rest part of the document is organized as follows: A brief literature review of 3D reconstruction methods is given in Section II. Section III discusses the system architecture and its configuration, image capturing procedure, depth computation, stereo image rectification, and target object identification. 3D reconstruction procedure with disparity map is presented in IV, and finally, the conclusions are in V.

## 2. PREVIOUS WORKS ON 3D RECONSTRUCTION AND STEREO IMAGING SYSTEM

Jingchao Li et al. [9] proposed point clouding-based surface reconstruction to obtain the visual hull from multiview stereo images. The on-machine 3D reconstruction method is proposed by Zhongren Wang et al. [2]. They reconstructed the 3 D shape of the on machine work piece via stereo matching and projective rectification. Xiong et al. [3] presented an automatic technique for 3D reconstruction system of historical sites. They used four-cameras to reconstruct the 3D shape. The additional cameras in this system improve the measurement accuracy. 3D object shape reconstruction from a sequence of frames has been developed using an inertial sensor [4]. In this system, the 3D shape is recovered using the tracking features of a video sequence. Newcombe et al. [5] described a 3D reconstruction method using a camera. The 3D model is reconstructed from depth maps. Kang and Szeliski [10] proposed a procedure to compute the disparity map and then obtained a 3-dimensional model of a scene using panoramic cylindrical mosaics. They captured the omni directional images by rotating and shifting the camera at different locations, and finally, cylindrical image mosaics were generated using these images. Bouguet et al. [7] presented an inexpensive approach for producing 3D information of objects using a special lighting condition and hardware like a lamp, pencil, and a checkerboard.


Figure 1. A schematic diagram of the proposed system.

Different types of stereo imaging systems have been developed for different applications. A method using a planar mirror has been presented by Xiao-Feng Feng [8] for measuring a 3D point. Carlos Jaramillo [11] developed a stereo imaging system with a high-resolution camera and two mirrors. These are placed inside an acrylic tube to capture the images. Nishimoto and Shirai[12] developed a system using a camera with a rotating glass plate. The plate is attached before the camera, and the stereo images are acquired from two different rotational positioned of the glass plate. This system is used only for the static scene because it requires two shots to capture two images.


Figure 2. Transformation steps from $3 D$ world coordinate to digital pixel coordinate.

## 3. ARCHITECTURE OF THE PROPOSED SYSTEM

## A. System description

A schematic diagram of the proposed system is depicted in Figure 1. The most complex part of the system is generating two stereo images using a camera and mirrors at the same instance. The 3D reconstruction is performed using the two images having the disparity between them. The 3D reconstruction process involves the following steps: (1) system calibration, (2) stereo image rectification, (3) object identification in the scene, (4) establishing a $1: 1$ correspondence between image points in the two images, (5) calculating the disparity between them for determining the object distance from the camera and finally (6) reconstruction of the 3-D point cloud.

In the 3D vision, camera calibration determines the set of camera parameters for mapping a 3D coordinate system from a 2D coordinate system. The camera parameters are calibrated to transform a 3D object coordinate into a two dimensional image coordinate. Figure 2. describes the different transformation steps.

Step I: Transformation from world coordinate system to mirror coordinate system.

Figure. 4. Illustrates the geometry of the proposed system. Here we consider the point $(X, Y, Z)$ as the 3D coordinate of the object point $P$ in the world coordinates system. A ray from the point $P$ is incidence at a point $M_{r}\left(X_{m r}, Y_{m r}, Z_{m r}\right)$ right mirror. $M_{r}$ is the 3D coordinate of the object point $P$ in the mirror coordinate system. World coordinate to mirror coordinate transformation is given by

$$
\left[\begin{array}{c}
X_{m r}  \tag{1}\\
Y_{m r} \\
Z_{m r}
\end{array}\right]=R\left[\begin{array}{c}
X \\
Y \\
Z
\end{array}\right]+T_{m}
$$

where $R$ is the $3 x 3$ rotation matrix and is given by,

$$
R=\left[\begin{array}{lll}
r_{00} & r_{01} & r_{02}  \tag{2}\\
r_{10} & r_{11} & r_{12} \\
r_{20} & r_{21} & r_{22}
\end{array}\right]
$$

and $T_{m}$, the translation vector is given by,

$$
T_{m}=\left[\begin{array}{l}
T_{m x}  \tag{3}\\
T_{m y} \\
T_{m z}
\end{array}\right]
$$

The transformation from world coordinate $(X, Y, Z)$ to mirror coordinate ( $X_{m r}, Y_{m r}, Z_{m r}$ ) is defined by a 3D rotation around the origin followed by a 3D translation.

Step II: Transformation from mirror coordinate to the camera coordinate

The camera coordinate is at the optical center of the camera and the line perpendicular to the $X Y$ plane of the camera coordinate system, and which passes through the optical center. To express an object point $M_{r}$ at location ( $X_{m r}, Y_{m r}, Z_{m r}$ ) in the mirror coordinate, we transform the mirror coordinate to the camera coordinate $((x, y, z)$. A point in mirror coordinate system $P_{m}$ can be transformed to a point in camera coordinate system $P_{c}$ by the following equation:

$$
\begin{equation*}
P_{c}=R\left(P_{m}-T_{m}\right) \tag{4}
\end{equation*}
$$

where $T_{m}$ is the translation of the object point. The transformation from the right mirror to the camera coordinate system is given by,

$$
\left[\begin{array}{l}
x  \tag{5}\\
y \\
z \\
1
\end{array}\right]=\left[\begin{array}{cccc}
r_{00} & r_{01} & r_{02} & 0 \\
r_{10} & r_{11} & r_{12} & 0 \\
r_{20} & r_{21} & r_{22} & 0 \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{cccc}
1 & 0 & 0 & -T_{m r x} \\
0 & 1 & 0 & -T_{m r y} \\
0 & 0 & 1 & -T_{m r z} \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{c}
X_{m r} \\
Y_{m r} \\
Z_{m r} \\
1
\end{array}\right]
$$

Similarly for left mirror, the camera coordinate transfor-
mation is given by,

$$
\left[\begin{array}{l}
x  \tag{6}\\
y \\
z \\
1
\end{array}\right]=\left[\begin{array}{cccc}
r_{00} & r_{01} & r_{02} & 0 \\
r_{10} & r_{11} & r_{12} & 0 \\
r_{20} & r_{21} & r_{22} & 0 \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{cccc}
1 & 0 & 0 & T_{m l x} \\
0 & 1 & 0 & T_{m l y} \\
0 & 0 & 1 & T_{m l} \\
0 & 0 & 0 & 1
\end{array}\right]\left[\begin{array}{c}
X_{m l} \\
Y_{m l} \\
Z_{m l} \\
1
\end{array}\right]
$$

Step III: Transformation from camera coordinate system to undistorted image coordinate system.

The convex mirrors used in this system may introduce some distortion in the image.Therefore, some corrections in the image coordinates are necessary to improve the reconstruction precision. Let $\left(x_{d}, y_{d}\right)$ and $\left(x_{u}, y_{u}\right)$ is the distorted and ideal undistorted image coordinates, respectively. Distortion $\left(d_{x}, d_{y}\right)$ is calculated by [13]

$$
\left[\begin{array}{l}
d_{x}  \tag{7}\\
d_{y}
\end{array}\right]=\left[\begin{array}{l}
x_{u} \\
y_{u}
\end{array}\right]-\left[\begin{array}{l}
x_{d} \\
y_{d}
\end{array}\right]
$$

and the radial distortion model can be expressed using the following expression:

$$
\left[\begin{array}{l}
d_{x}  \tag{8}\\
d_{y}
\end{array}\right]=\left[\begin{array}{l}
x_{d} \\
y_{d}
\end{array}\right]\left(r_{d}^{2} k_{1}+r_{d}^{4} k_{2}+r_{d}^{6} k_{3}+\ldots \ldots \ldots\right)
$$

where $r=\sqrt{\left(x_{d}^{2}+y_{d}^{2}\right)}$ and $k_{1}, k_{2}, k_{3} \ldots \ldots$. are the distortion coefficients. From equation (8) we can map distorted points to undistorted image points.

$$
\left[\begin{array}{l}
x_{u}  \tag{9}\\
y_{u}
\end{array}\right]=\left[\begin{array}{l}
x_{d} \\
y_{d}
\end{array}\right]\left(1+r_{d}^{2} k_{1}+r_{d}^{4} k_{2}\right)
$$

Step IV: Transformation from image coordinate system to digitized pixel coordinate system.

Image coordinates are expressed in terms of pixel locations [14]. Let us assume for a pixel at the position $(u, v)$, the camera coordinate to digital image coordinate can be expressed as follows;

$$
\left[\begin{array}{l}
u  \tag{10}\\
v \\
1
\end{array}\right]=\left[\begin{array}{ccc}
-1 / s_{x} & 0 & c_{x} x \\
0 & -1 / s_{y} & c_{y} \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{c}
x_{u} \\
y_{u} \\
1
\end{array}\right]
$$

In the above equation, $\left(c_{x}, c_{y}\right)$ represents the center of the image and $s_{x}, s_{y}$ are scale factors in the horizontal and vertical directions respectively.

## B. Depth Computation

Figures 3 and 4 show the system setup and the ray diagram of the proposed system with respect to the coordinate system given in equation (11) [15], [16].


Figure 3. System configuration.

Figure 4. This figure shows system design and ray diagram.

The disparity and the depth of the object relationship can be computed as

$$
\begin{equation*}
Z=\frac{\left(Z_{m}-\lambda\right)}{\left(Z_{m}-\lambda+F\right)}\left\{\left(Z_{m}-\lambda+2 F\right)+\frac{F \delta X \lambda}{2\left(Z_{m}-\lambda+2 F\right) d}\right\} \tag{11}
\end{equation*}
$$

where $d=x_{l}-x_{r}$ disparity between left and right image. $k_{1}=Z_{m}-\lambda$ distance from the camera to the joining edge of the convex mirrors.
$\lambda=$ focal length of the camera.
$F=$ focal length of the mirrors.
$\delta X=$ baseline .


Figure 5. Epipolar geometry between left image and right image.

## C. Stereo image rectification

Stereo image rectification [25] is an essential preprocessing step for computing disparity between two images because it converts 2D correspondence problems to 1D search along conjugate epipolar lines. In general, epipolar lines are not parallel with the coordinate axis. The stereo correspondence becomes more simplified and efficient if epipolar lines are aligned and parallel with the axis. To understand the stereo image rectification, consider a 3D object point which is to be projected at $p_{l}\left(x_{l}, y_{l}\right)$ in the left image plane and at $p_{r}\left(x_{r}, y_{r}\right)$ in the right image plane (Figure 5). These two points should lie on a same horizontal or epipolar line. Figure 5. depicts the epipolar geometry between left and right image. The condition for which the points $p_{l}$ and $p_{r}$ will be on the same epipolar line is given by,

$$
\begin{equation*}
p_{r}^{T} F p_{l}=0 \tag{12}
\end{equation*}
$$

Where F is the fundamental matrix that maps points in left image $I_{l}$ to lines in right image $I_{r}$ and points in right image $I_{r}$ to lines in left image $I_{l}$. If $p_{l}$ is a point in $I_{l}$ then $F p_{l}=l_{r}$ is an epipolar line in $I_{r}$. In particular, any point $p_{r}$ that corresponds to $p_{l}$ must line on the epipolar line $F p_{l}$. For a fundamental matrix $F$, the epipoles for the left image $e_{l}=\left(e_{l x}, e_{l y}, 1\right)^{T}$ and right image $e_{r}=\left(e_{r x}, e_{r y}, 1\right)^{T}$.

$$
\begin{equation*}
F e_{l}=0=F^{T} e_{r} \tag{13}
\end{equation*}
$$

The epipolar constraint can be defined

$$
\begin{equation*}
p_{r} K_{c}^{-T} \hat{T} R K_{c}^{-1} p_{l}=0 \tag{14}
\end{equation*}
$$

where fundamental matrix, $F$ is given by,

$$
F=K_{c}^{-T} \hat{T} R K_{c}^{-1}
$$

and the translation vector

$$
\hat{T}=\left[\begin{array}{ccc}
0 & -t_{z} & t_{y} \\
t_{z} & 0 & -t_{x} \\
-t_{y} & t_{x} & 0
\end{array}\right]
$$

Equation (14) expresses the coplanarity between any two points $p_{l}$ and $p_{r}$ on the same epipolar plane. If $p_{l}$ is fixed in image $I_{l}$, then any point $p_{r}$ in image $I_{r}$ for which equation (11) must be on the epipolar line of $p_{l}$. Figure 6 shows the rectified image pair.

## D. Object identification

Proper image segmentation is used for detecting the objects in the scene, for 3D reconstruction. Image segmentation is partitioning images into multiple regions (especially connected pixels). In this process, we generally assign a label to every pixel of the image such that the same label may assign the pixels that belong to the same region. Many image segmentation techniques are available. Each has its own merits and demerits depending on computational complexity and segmentation accuracy. This work has selected a marker based watershed algorithm for object segmentation. In the conventional watershed algorithm, gray scale images are considered topographic surfaces. A flooding mechanism is simulated starting from local minima. A flooding level is considered. This flooding level is the same for the whole image, the pixels with values lesser than belonging to a dam. When two dams meet, a wall is made between the dams. This wall forms the watershed line. When the whole image is flooded, it generates watershed lines as many regions as local minima present in the image. These regions are called catchment basins. By generating watershed lines, different regions of an image are segmented. Since no threshold value is used in this case, the main advantage "lacking precision" of the threshold-based segmentation is avoided. But the main disadvantage of the conventional watershed algorithm is that it results over-segmentation if the image is noisy. To overcome this problem, marker-controlled watershed method has been proposed [17]. In this method, the region of the foreground or object is labeled with one color, the background or non-object is labeled with another color and finally, the region which are not clearly defined, are labeled with 0 . That is defined as a marker and applies the watershed algorithm.


Figure 6. (a) and (b) Stereo images captured by the system. (c) Rectified image pair of left and right image. A horizontal line is added to the rectified images to check the rectification.

## 4. Disparity map and 3d reconstruction

Finally, a method to reconstruct the 3D model of an object has been proposed. For 3D reconstruction, the disparity between the images is computed by finding the corresponding points of the two images. The disparity map is then constructed by using the disparity values. The construction of a disparity map is one of the most important parts of 3D reconstruction. The disparity may be computed by applying a feature-based (global) or correlation-based (local) algorithm.

In the correlation-based method, the disparity map is produced by calculating the disparity. In this category sum of absolute differences (SAD) [18] is used as dissimilarity for computing disparity. It computes the intensity differences of each pixel between the $I_{r e f}$ and the $I_{t a r}$ in a fixed size window as follows:

$$
\begin{array}{r}
S A D(x, y, d)=\sum_{i=1}^{W_{x}} \sum_{j=1}^{W_{y}} \mid I_{r e f}(x+i, y+j) \\
-I_{\text {tar }}(x+i+d, y+j) \mid \tag{15}
\end{array}
$$

Sometimes sum of squared differences (SSD) [19] is used as dissimilarity measure. However, this method suffers from higher computational complexity compared to SAD.

$$
\begin{align*}
S S D(x, y, d)= & \sum_{i=1}^{W_{x}} \sum_{j=1}^{W_{y}} \mid I_{r e f}(x+i, y+j) \\
& -\left.I_{t a r}(x+i+d, y+j)\right|^{2} \tag{16}
\end{align*}
$$

Though these window-based algorithms produce accurate depth maps and are widely used in solving correspondence problems, the availability of specific rules for selecting the window makes them unpopular in many applications. In these algorithms, the performance and the time complexity differ for different window sizes.

Feature-based algorithms use object features (such as lines, edges, corners, geometric figures, etc.) to match the corresponding images for computation disparity. The best matches are found out through an iterative process in these algorithms. These algorithms provide a better performance, but computational complexity is more. Since we need a sufficiently accurate disparity map for 3D reconstruction, we choose a feature-based algorithm to generate the disparity map. In a feature-based algorithm [20], a global cost function is minimized. The cost function in this algorithm contains- both data and smoothness terms and is given by,

$$
\begin{equation*}
E(f)=E_{\text {data }}(f)+E_{\text {smooth }}(f) \tag{17}
\end{equation*}
$$

The data term $E_{\text {data }}(f)$ is the pixel difference between the $I_{r e f}(p)$ and $I_{t a r}\left(p+f_{p}\right)$.

$$
\begin{equation*}
E_{d a t a}(f)=\sum_{p \in P}\left|I_{r e f}(p)-I_{t a r}\left(p+f_{p}\right)\right|^{2} \tag{18}
\end{equation*}
$$

The smoothness term is used to calculate the disparity smoothness within the neighboring pixels. $f_{p}$ is the disparity value for a pixel $p$ in the left image.


Figure 7. 3D Reconstruction of the object

$$
\begin{equation*}
E_{\text {smooth }}(f)=\sum_{p, q \in N} V_{p, q} \cdot T\left(f_{p} \neq f_{q}\right) \tag{19}
\end{equation*}
$$

The depth $(Z)$ of each point of the objects is computed using equation (10), and the disparity is determined using a featured-based algorithm. The depth image, which sometimes is called point clouds or gray scale images, has been used to generate the 3D shape and position of an object. Figure 7,8 and 9 show the three objects in captured images, their 3D reconstructions and the disparity maps form different viewpoint.

To demonstrate the effectiveness of the system, an interface module is implemented using Microsoft Foundation Class with Visual C++ environment. The image processing tasks and the computations of disparity is accomplished by the 3 GHz computer with 2 GB RAM. The 3D reconstruction process involves the (1) stereo images capturing by the proposed system, (2) stereo image rectification, (3) object identification in the scene, (4) calculating the disparity between the left and right images for generating disparity map and finally (5) reconstruction of the 3-D point cloud. In this paper, we have used a low-resolution camera in the proposed system and thus to complete the 3D reconstruction process needs near about 100 ms .


3D reconstruction of the object
Figure 8. 3D Reconstruction of the object


## 5. Conclusions and Future Work

This paper has proposed a 3D shape reconstruction system. The system is a stereo vision system that consists of one camera, two mirrors, and a computational unit. The convexity of the mirrors can provide a wider field of view. The selection of a large curvature radius helps the system form a less distorted image. No calibration of the system and -synchronization is required since only one camera has been used. 3D reconstruction of a target object has been performed by computing a disparity map and using -the 3D point clouding technique. The system's performance is verified by identifying different objects of different shapes and sizes from captured stereo images. The use of the single camera in the stereo vision system has made it simple in construction and lesser expensive.

Though the proposed system is a low-cost system with a simple design and may be used effectively for 3D reconstruction, still there are some limitations of our proposed system. The limitations are 1) the captured stereo images may have small distortion, which may affect the accuracy in measuring the disparity. Consequently, the measurement of all other parameters may be affected by errors in the disparity map. 2) Since the camera captures two images of a scene in a particular area, the resolution of stereo images is becoming lower. 3) In the depth map, sometimes a few black holes are generated where the information about those points are not obtained. 4) When the objects is located near the boundary line of the field of view, there is a chance of missing the object from one of the stereo images, which is called occlusions.

For future endeavors in this research, some recommendations are suggested like 1) to improve the design of the system for making it compact and light weight. 2) More research work should be carried out to remove the artefacts (black holes) from the disparity map and avoid the effect of occlusion problems in the measurement of depth and 3D reconstruction of objects from the stereo images. 3) To estimate the depth information in challenging environment such as night time, foggy day, rainy day etc.

## References

[1] W. Jing Chen, Wenqiang Xu, "Stereo vision-based -real-time localization of electric vehicle battery in the -complex environment," Advanced Robotics, pp. 1050-1060, 2016.
[2] Y. Zhongren Wang, Fan Zhang, "3d reconstruction based on stereo vision and texture mapping," Second International Symposium on Information Science and Engineering, 2009.
[3] Z. L. Xiong J., Zhong S., "An automatic 3d reconstruction method based on multi view stereo vision for the mogao grottoes," ISPRS International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 62, pp. 171-176, May. 2015.
[4] N. O. T. Mukai, "3d reconstruction based on stereo vision and texture mapping," in Proceedings of the 7th International Confer-
ence on Computer Vision (ICCV-99), 1999, Kerkyra, Greece: IEEE Computer Society Press., Sep. 1999.
[5] A. D. R. Newcombe, S. Lovegrove, "Dtam:dense tracking and mapping in real-time," In ICCV, pp. 2320-2327, Nov. 2011.
[6] M. D. F. D. P. S. E. Mouragnon, M. Lhuillier, "Real time localization and 3d reconstruction," 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), pp. 363-370, 2006.
[7] J. B. P. Perona, "3d photography on your desk," in International Conference on Computer Vision, Bombay, pp. 43-50, 1998.
[8] X. feng Feng and D. fu Pan, "Research on the application of single camera stereo vision sensor in three dimensional point measurement," Journal of Modern Optics, vol. 62, pp. 1204-1210, Feb. 2015.
[9] X. L. Y. W. Jingchao Li, Zhenjiang Miao, "3d reconstruction based on stereo vision and texture mapping," Proceedings of the ISPRS Technical Commission III Symposium, Photogrammetric Computer Vision and Image Analysis, Paris, France, vol. 1, pp. 1-6, Sep. 2010.
[10] R. S. S. B. Kang, "3-d scene data recovery using omnidirectional multi baseline stereo," In Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR ' 96), San Francisco,, pp. 364-370, Jun. 1996.
[11] J. Carlos Jaramillo, Ling Guo, "A singlecamera omni-stereo vision system for 3d perception of micro aerial vehicles( mavs)," 8th IEEE Conference on Industrial Electronics and Applications (ICIEA), Melbourne, VIC, p. 1409 - 1414, 19-21 Jun 2013.
[12] Y. S. Y. Nishimoto, "A feature-based stereo model using small disparities," in Proc. Of Int. Conf. on Computer Vision and Pattern Recognition,Pentland, pp. 192-196, 1987.
[13] M. Trobina, "Error model of a coded-light range sensor," Technical Report BIWI-TR-164, ETH-Zentrum, 1995.
$[14]$ B. L. J. Park, S. Byun, "Lens distortion correction using ideal image coordinates," IEEETrans. Consumer Electron, pp. 987-991, Aug. 2009.
[15] N. D. Murmu. N, "Low cost distance estimation system using low resolution single camera and high radius convex mirrors," 2014 IEEE International Conference on Advances in Computing, Communications and Informatics, (ICACCI), Delhi, India, pp. 9981003, 24-27 Sep 2014.
[16] N. D. Murmu N, Chakraborty B, "Relative velocity measurement using low cost single camera-based stereo vision system," Measurement, pp. 1-11, 2019.
[17] S. B. Meyer Fernand, "Morphological segmentation, journal of visual communication and image representation," 2014 IEEE International Conference on Advances in Computing, Communications and Informatics, (ICACCI), Delhi, India, pp. 21-46, Sep. 1990.
[18] A. B. U. Chirag S. Panchal1, "Depth estimation analysis using sum of absolute difference algorithm," International Journal of Advanced Research in Electrical,Electronics and Instrumentation Engineering,, pp. 21-46, Jan. 2014.
[19] M. R. B. M. M. Maged Marghany, "3d stereo reconstruction using
sum square of difference matching algorithm," Scientific Research and Essays,, pp. 6404-6423, Dec. 2011.
[20] V. Yuri Boykov o, "Fast approximate energy minimization via graph cuts," IEEE TRANSACTIONS ON PATTERN ANALY- SIS AND MACHINE INTELLIGENCE,, pp. 1222-1239, 2001.


Narayan Murmu received his BE degree in Information Technology from Jadavpur University, Kolkata, India, in 2004. He received his PhD degree from NIT Durgapur, India, on Computer Vision.

Debashis Nandi received his BE degree in ECE from NIT Durgapur, India, in 1994. He received his PhD degree from IIT, Kharagpur, India, on Medical Imaging Technology. He is now professor in the Department of CSE, NIT, Durgapur, India.

