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Original Article

Development of an Algorithm for Volumetric Reconstruction and Estimation of the Center of Mass of Solid Cohesive in Environments with Suspended Particles

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Abstract - *Volumetric reconstruction is a research niche that has attracted attention due to the large number of applications. There are several techniques to extract a point cloud from a scene, but stereo vision is the most recognized technique. Volumetric reconstruction is a research niche that has attracted attention during the last decade due to its many applications. There are several techniques to extract a point cloud from a scene, but the most recognized technique is stereo vision. Stereo vision uses two images of a set to calculate the distance of the objects from the cameras; however, in most reviewed works, this occurs in clean environments and with controlled lighting. This paper presents an algorithm capable of estimating a point cloud of some object in cloudy environments with suspended particles to subsequently approximate the center of mass of the entity for mining comminution applications.*

Keywords - *Volumetric reconstruction, Center of mass, Stereo vision, Dehazing algorithm, 3D image.*

1. Introduction

Tasks such as object detection and classification and detection of shapes, colours and sizes are activities humans do using their eyes. Since the creation of cameras, it has been proposed that machines and computers can perform the same actions. During the last decade, it has been suggested that devices and computers can achieve 3D reconstructions of scenes and objects to achieve accurate grasping of things and autonomous driving interpretation of clinical photographs, but unfortunately, acquiring a scene's depth is not a simple task [1]. To extract the 3D structure of a set or object, there are various techniques and sensors, such as Time-of-Flight (ToF) sensors, laser triangulation, structured light, and stereoscopic vision [2, 3].

Although 3D sensing devices are increasing in popularity among the community and reducing in price, 3D sensing technologies still have certain limitations (mentioned in [3]); therefore, users must choose the sensor type to meet their objectives. Although ToF sensors are inexpensive and quick to respond [4], they can be prone to errors such as noise, ambiguity and unsystematic errors such as scattering and motion blur [3, 5]. In addition, ToF devices are susceptible to environmental conditions such as lighting and temperature, and the accuracy of the sensors decreases as the measurement distance increases [4, 5]. On the other hand, laser triangulation sensors have high precision and lower environmental sensitivity; however, they are expensive compared to other sensors, experts must handle them to operate, and users must remain still during the capture process [3]. In turn, structured light sensors were not designed to be of high quality, so they tend to have high noise levels that affect their accuracy [3].

Finally, Stereoscopic Vision (SV), which is undoubtedly one of the pioneering and most popular techniques for capturing 3D images [6], bases its operation on matching the characteristics of two images of an object and then combining both ideas by triangulating the distance between the cameras and the distance from the scanned object to form the 3D image [6].

SV systems present the advantage that they do not require additional equipment to capture depth information, it is a mature, robust and reliable technology, however, it presents limitations such as occlusions, ambiguities and image illumination. Many challenges of SV were addressed and solved by researchers, these are discussed in [7-9]. With the above described, it is evident that 3D reconstruction is a problem not yet solved and that the technique and sensor to be applied depend very much on the environmental conditions. The algorithms developed up to the present year (described in the following section) achieve the 3D reconstruction of objects, but in relatively clean and straightforward scenarios; on the other hand, our work pretends to solve the problem of volumetric reconstruction in hostile environments, where there are conditions of extreme luminosity and particles in suspension in the background using low-cost elements.

The work is oriented for mining comminution applications, where a hostile environment is present, with strong wind gusts and significant differences in temperature and illumination between day and night. For this reason, the use of ToF sensors is suppressed because they are sensitive to lighting and temperature, the use of laser triangulation sensors is discarded due to their high cost and the use of structured light sensors is avoided due to their low accuracy.

Therefore, for the development of this work, stereo vision will be used due to its excellent support and diverse solutions offered; in addition, thinking of giving continuity to the process and avoiding the effects of sun illumination, an SV system using Infrared (IR) cameras will be used.

On the other hand, considering reducing the energy consumed during the fractionation of the rocks, the center of mass is estimated from the 3D reconstruction so that a rock hammer can perform an accurate blow to split the stones later. Therefore, the contribution of this paper highlights the 3D reconstruction using an SV system employing IR cameras in environments with suspended particles and, subsequently, the estimation of the center of mass of the reconstructed solid.

The rest of the paper is organized as follows: Section 2 presents the state of the art related to volumetric reconstruction, Section 3 presents the proposed algorithm, Section 4 presents the results, and Section 5 presents the conclusions of the work.

2. Related Works

The most recent works on volumetric reconstruction point to the use of Artificial Intelligence (AI) on monocular images; unfortunately, this is an ill-posed problem since there is no unique solution due to the information lost from the 3D to 2D projection and due to the occlusion problem [10]; however, researchers developed techniques to work directly with 3D data and achieve tasks such as pose estimation, completion, classification, recovery, reconstruction and generation of 3D shapes. AI techniques represent 3D information as voxels, point clouds, octrees or 3D meshes, as shown in Figure 1; for more information about 3D information representation, the reader is referred to [10-13].

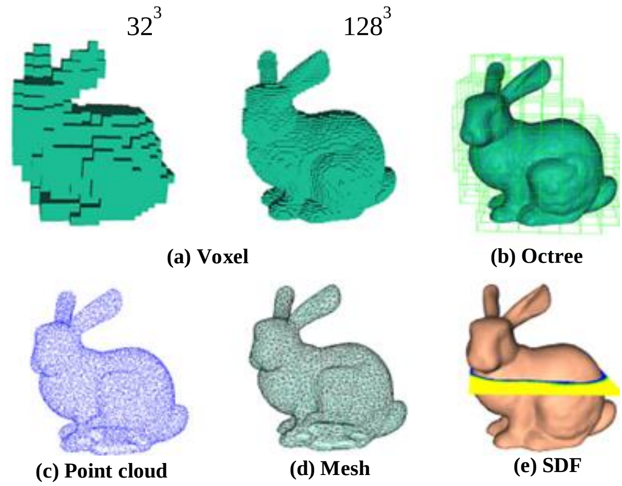


Fig. 1 Representation of 3D information [10]

One of the pioneering works in single-view 3D reconstruction is 3D-R2N2 [14], a 3D-Reconstruction Recurrent Neural Network capable of obtaining an output voxel from a single view and refining the rebuilding from the input of more pictures of the object in question for this, they make use of neural network type Long Short Term Memory (LSTM).

The architecture of the network is composed of three modules, an encoder, which extracts the features of the input image; a 3D-LSTM module in charge of retaining and updating the features when a new image is entered; and a decoder, which transforms the 3D-LSTM states into a voxel occupancy map.

A work that presents as output an octree can be seen in [15]; this method offers octrees with low noise and can reconstruct occluded regions and fill gaps in the reconstruction; for this, Riegler et al. [15] propose a step from coarse to fine using pyramid where the resolution is increased at each stage. Each pyramid level consists of an encoder-decoder module that expands the receptive field and captures contextual information, which is then passed to a structure manipulation module that increases the resolution and updates the network structure for further processing.

The work proposed by Johnston et al. [16] abandons the encoder-decoder architecture, replacing the decoder with the Inverse Discrete Cosine Transform (IDCT), which gives the algorithm higher speed and lower consumption of computational resources. An improved version of 3D-R2N2 can be found in the work of Xie et al. [17]; the authors propose a network for a single-view and multiview 3D reconstruction, which contains four modules, encoder, decoder, context-sensitive fusion and refiner. The encoder and decoder perform the same functions as 3D-R2N2. Still, the various reconstructions enter the context-sensitive fusion module, which scores the previously obtained voxels, merges the volumes into one, and then enters the refiner, correcting incorrectly recovered parts in the 3D volume.

A different approach is seen in [18], who use Generative Adversarial Networks (GAN) to predict a volume from a single view using voxels. The reconstruction is improved by applying 2D projection masks, which are then compared with authentic masks input to the network. The proposed network has constraints on object background and scene illumination.

In [19], they propose a hybrid approach using voxel combinatorics and point clouds. The proposed method consists of using volumetric voxel learning and adopting sparse point cloud learning to improve the accuracy of the model because obtaining point clouds is computationally expensive but presents high-resolution outputs; on the contrary, generating voxels gives lower computational consumption but lower output resolution, a hybrid approach improves the solution and the consumption of computational resources.

Bin Li et al. [20] developed 3D-ReConstNet, a network capable of generating a point cloud from a single view and multiple views when the input image is ambiguous. The designed network presents three modules, a feature extraction module, where the ResNet-50 network is used to extract features, a probabilistic vector sampling module, where the standard deviation and the average of the data are approximated to obtain a Gaussian function; and finally, a point cloud generation module.

The purpose of this document is not to provide an in-depth analysis of all the algorithms developed for volumetric reconstruction. If the reader wishes to learn more, they can refer to [10, 21, 22]. However, Artificial Neural Networks (ANN) for 3D reconstruction are still in an early phase, and there are no ANN-based approaches for reconstructing unknown or unseen 3D objects and scenes [23]. Additionally, neural networks do not accurately provide the 3D coordinates of the point in question. These are the reasons why an SV system is used for 3D reconstruction.

On the other hand, SV systems are much more reliable and have diverse applications in many types of industries; it can be mentioned control of underwater vehicles [24], obstacle detection [25, 26], medical applications [27], autonomous navigation, etc. In mining, SV systems are used mainly for route planning [28] and rescue robots [29].

On the other hand, the centre of mass approximations is only used to solve problems in robot controllers as proposed by [30-33]; in the current work, the task is a bit simpler, since only want to estimate the centre of mass of a cohesive solid to impact on that point subsequently, therefore, if have available the point cloud of the object in question it would only be enough to apply the equations available in classical mechanics books shown in Equation (1) [34].

$$x = \frac{\sum_i m_i x_i}{\sum_i m_i},\ y = \frac{\sum_i m_i y_i}{\sum_i m_i},\ z = \frac{\sum_i m_i z_i}{\sum_i m_i} \tag{1}$$

Where (x, y, z) is the position of the center of mass, (x_i, y_i, z_i) is the position of each point of the point cloud, and m_i us the mass of each point. It is essential to mention that for this work, is considered to work with homogeneous density solids. It can be seen in the literature reviewed that there are no applications of volumetric reconstruction of solids using IR cameras and neither the approximation of the center of mass of 3D volumes for mining processes.

3. Proposed Work

The proposed work consists of achieving 3D reconstruction utilizing an SV system with IR cameras in environments with suspended particles and then estimating the center of mass of the solid so that a rock hammer can accurately impact it.

The technique employed consists of acquiring the images clouded by the suspended particles, applying the Fast Dark Channel Prior algorithm (described in [35]), various filters and the Semi-Global Block Matching (SGBM) algorithm to obtain the disparity map. The disparity map will be segmented to extract the rock to be reconstructed. The segmented region calculates its centroid, which will be projected as the centre of mass of the solid under study. The complete algorithm with all its steps can be visualized in Figure 2.

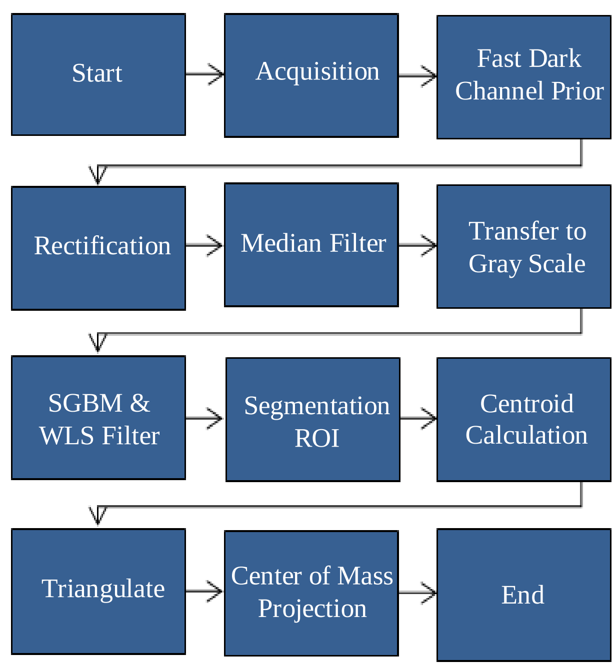


Fig. 2 Proposed algorithm

Along with the proposed algorithm, a test environment has been developed to implement the algorithm, consisting of a closed system of 120x50x30 centimetres (cm), with two IR cameras on top with a resolution of 360x640 pixels (px). On the side is a pipe where the particulate material is deposited, impulsed by an air current produced by the blower. When the air current meets the particulate material, it creates a dust cloud that reduces the visibility of the cameras. A graphic representation of the system under study is shown in Figure 3. Figure 4(a) and 4(b) show the images captured by the cameras with and without particles in suspension.

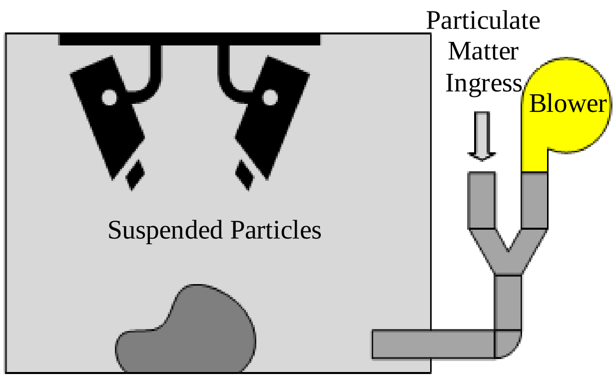
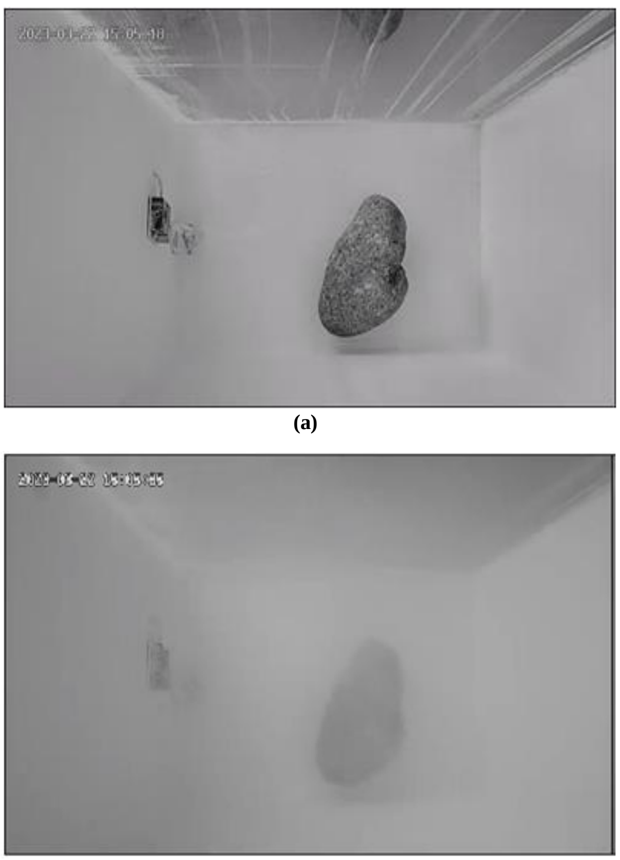


Fig. 3 Proposed experiment



(a)

(b)

Fig. 4 Images captured by the left camera, (a) Image without particles in suspension, and (b) Images with particles in suspension.

It is essential to mention that the images clouded by dust are captured ten seconds after the dust cloud has been lifted; otherwise, the photos are too blurry to be processed. It should also be noted that the material used to lift the cloud of dust corresponds to 5 grams of talc. This is because talc has textural qualities and appearance very similar to dust. The results of the proposed algorithm and an analysis of it will be reviewed in the next section.

4. Results and Discussion

Once the dust cloud is lifted, we must wait for the necessary time and capture the images entering the algorithm shown in Figure 2. It is essential to mention that a fundamental step in the algorithm is obtaining the disparity map, which is obtained after running the SGBM algorithm and the WLS filter. Figure 5 shows the result when entering Figure 4(b) into the proposed algorithm.

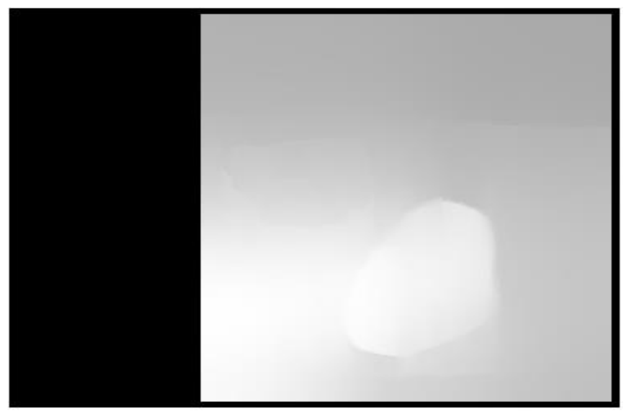


Fig. 5 Disparity map

Then, the disparity map of Figure 5 is segmented using the Lazy Snapping algorithm (described in [36]), which, with the help of the user, allows the rescue of the object of interest. Subsequently, the centroid of the segmented object is calculated; this point will be projected as the center of mass of the reconstructed point cloud. Figure 6 shows the segmented thing with its centroid.

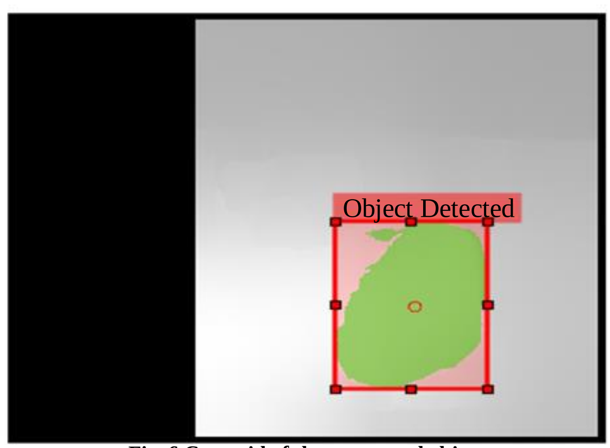
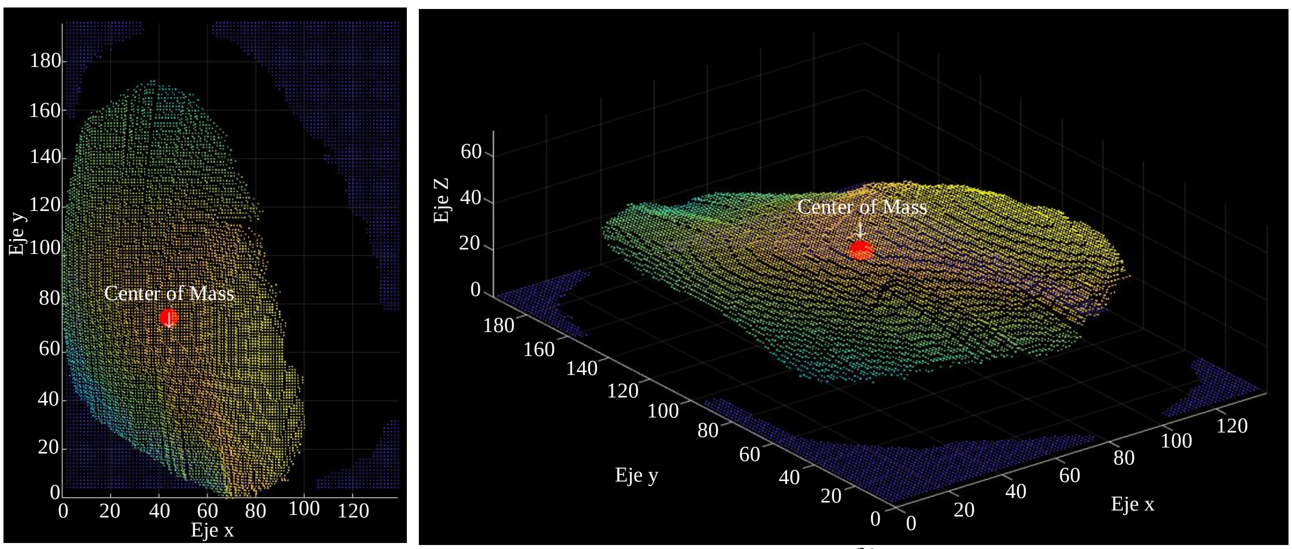


Fig. 6 Centroid of the segmented object

The triangulation technique is applied to the segmented object to obtain the volumetric reconstruction of the thing under study. Knowing the position of the centroid, it is possible to rescue the disparity value of that position and project it in the point cloud as the centre of mass. Figure 7 shows the point cloud and the centre of mass estimation as a red point. Then, both measurements can be compared, and the absolute and percentage errors of the algorithm measurements can be calculated. Table 1 summarizes this information.

It can be observed that the most significant error in the measurement is found in the height of the rock, presenting a 10.6% error in this measurement; this is because the dust cloud and the applied filters erase the characteristics and textures of the surface of the object, this difficult the process of stereo correspondence and finally the process of triangulation, with which the dimensions of the rock are extracted. On the other hand, the minimum errors are found in the length and width dimensions; this is because the filters applied highlight the objects' edges, not the interior's texture, thus facilitating the matching process. Although the rock presents a more significant estimation error in height, the average of the dimensions does not exceed 6% error, which would be acceptable for a mining comminution process. It can also be seen that the point cloud only shows the object's surface and not the details underneath, which is why the floor of the thing is displayed in blue. This is due to an innate problem of SV systems known as occlusion, which limits the 3D reconstruction of the object only to the part visible in the photos.

Tests with different morphologies and sizes affirm that the most significant error is in the height of the rocks. The above description proves that stereo-matching is the most critical when obtaining a volumetric reconstruction. This process requires that the images have enough texture to generate a correct disparity map.



(a) (b)

Fig. 7 Point cloud and center of mass estimation, (a) Top view, and (b) Isometric view.

(a) (b) (c)

Fig. 8 Real dimensions of the rock, (a) Height, (b) Width, and (c) Length.

Table 1. Comparison of the dimensions of the object in the study

Parameters	Real Rock Size (mm)	Approximate Rock Size (mm)	Absolute Error (mm)	Error (%)
Height	80	71.52	8.48	10.6
Large	200	198.23	1.77	0.88
Width	150	141.42	8.58	5.72
Mean			6.27	5.73

5. Conclusion

It can be seen that it is possible to achieve volumetric reconstruction in environments clouded by suspended particles and to estimate the center of mass with reasonable accuracy. As mentioned above, the most significant difference between the reconstructed point cloud and the real object under study will always be the shape of the surface and the height because the dust cloud and the applied filters remove the surface features, which makes it complex to obtain the disparity maps, which is why the application of the WLS filter becomes necessary. The length and width dimensions will always present a minor error because the WLS filter corrects the disparity map with one of the incoming images, producing edge enhancement but texture loss within the object. For this particular case, the centre of mass should be inside the object.

Still, in the context that a rock hammer will then impact the thing, the centre of mass coordinate cannot be inside the object under study, so it is entirely feasible to estimate this as a point on the surface of the object under investigation.

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