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Segmentation of overlapping particles in automatic size analysis using multi-flash imaging

Tze K KOH
Singapore Management University, andrewkoh@smu.edu.sg

Nicholas MILES

Steve MORGAN

Barrie HAYES-GILL

Image Segmentation of Overlapping Particles in Automatic Size Analysis Using Multi-Flash Imaging

Tze Ki Koh, Nicholas Miles
School of Chemical, Environmental and Mining Engineering

Steve Morgan, Barrie Hayes-Gill
School of Electrical and Electronics Engineering

University of Nottingham
University Park, Nottingham NG7 2RD, UK
{enxtkk, nick.miles, steve.morgan, barrie.hayes-gill}@nottingham.ac.uk

Abstract

In this paper, we propose a novel hardware approach to image segmentation, specifically in the case of overlapping particles. Our research is based on Multi-Flash Imaging (MFI), originally developed to detect depth discontinuities. Multiple images captured with different illumination conditions provide additional information about a scene compared to conventional segmentation techniques. Shadows are used to identify true object edges and underlying particles. We applied the new approach in automated particle size analysis and evaluated it against the watershed and canny edge detection techniques. Evaluation results confirm that MFI can be applied in image segmentation and reveals the superiority of the approach against conventional techniques in the case of overlapping particles.

1. Introduction

Image segmentation is an intrinsic determinist in the performance of computer vision applications as it directly influences the efficiency of subsequent image processing steps. Accurate identification of the region(s) of interest in an image is critical if one were to perform image analysis successfully. Numerous approaches and techniques have been developed to meet this need over the past few decades [2][4][9]. However, due to the diversity and complexity of scenes, there is no single technique which works effectively for every application [15].

In this paper, we discuss image segmentation with a specific emphasis on scenes containing overlapping particles. This is relevant to a wide range of applications, extending from analyzing grains in the food industry [12] to rocks in the mining industry [1]. Overlapping particles often pose a difficult task to image segmentation techniques due to the lack of discontinuity between particle edges, especially if they are of similar textures. While devices have been introduced to mechanically separate the particles before imaging [3], it may be too impractical a solution in some cases or impossible in others. An effective computer vision based technique to segment overlapping particles would thus prove to be very useful.

We introduce a novel approach to image segmentation based on Multi-Flash Imaging (MFI) developed by Mitsubishi Electric Research Labs [10]. Raskar *et al* made use of strategically positioned flashes to produce an edge depth map computed from a series of images taken with different illumination configurations. In this paper, we exploit the idea of shadows cast along different directions in a scene to accentuate object edges and utilize this information to increase the accuracy of image segmentation. In addition, MFI provides the ability to perform size analysis only on fully visible particles.

We evaluate the effectiveness of using MFI for image segmentation of overlapping particles in the context of automated particle size analysis in the mining industry. In Section 2, the background of the application area is discussed while Section 3 describes the original MFI algorithm and how we extend it for use in the segmentation of particles. Section 4 describes how we evaluated MFI against conventional segmentation techniques. Finally, conclusions and future work are presented in Section 5.

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2. Application domain

2.1. Automated particle size analysis

An accurate calculation of the size distribution of particles is crucial in the mining and quarrying industry. It is used to assess the quality of particulate material after or prior to operations such as crushing or blasting. Sieving is a traditional method where particles are passed through grids of variable mesh sizes to determine their size distribution based on their diameter. These systems require representative samples to be taken, with the inherent errors that this can involve. Offline analysis also means that the data collected is out of date. This has a significant impact where out of specification or contaminating materials are loaded into the wrong bunkers for example.

Therefore, online systems are often used in industrial situations to constantly monitor product characteristics, such as particle size. This is achieved with computer vision where cameras collect images of the product at some point in the process. The images are then subjected to some form of digital processing to extract relevant information. Such information might include particle shape or size distribution, which might form a product specification or provide information for materials handling calculations.

Computer vision in automated particle size analysis has been an active research area for many years [6][7][8][11][14]. It has obvious advantages over traditional mechanical sieving methods which are labour and time intensive. Accurate calculations are strongly dependent on the efficiency of the image processing steps, particularly image segmentation. Even if a proficient mathematical processing algorithm was used to produce a size distribution of an image with poorly segmented particles, the results would be inaccurate due to poor quality data input to the size processing algorithm.

2.2. Image segmentation and MFI

Image segmentation remains a challenging task in the area of computer vision. Each segmentation technique has its own strengths and weaknesses. Segmentation techniques often rely on intensity changes in an image to detect edges. As particles often have a similar surface texture, it is non-trivial to distinguish between overlapping particles. In addition, the texture contains intensity and color variations which are easily misinterpreted as false edges.

Amongst the systems reviewed [6][7][8][11][14], emphasis have been on using software based approaches to improve image quality prior to segmentation and also post-processing to correct for segmentation errors. Wang and Stephansson [14] used filtering and morphological operations to enhance the contrast between touching particles, remove bright spots and smooth grayscale variations. Methods to merge and split regions based on their common boundary and arc lengths were described.

Salinas *et al* [11] employed marker-controlled watershed techniques. The authors used a combination of morphological operations in the selection of markers. The experimental results, however, showed a significant discrepancy between the measured and true size distributions. These inaccuracies were attributed mainly to poor contrast between touching particles and texture variations within the surface area of each particle. The efficiency of the technique also relied heavily on the marker selection, which suggests a dependency on manual intervention.

Classifiers have been used to eliminate irrelevant regions from the watershed technique [8]. Features based on region shape, edge and intensity characteristics are used to train a classifier to identify regions where a particle truly exists or whether its part of the background. However, training of the classifier involves human judgment which introduces a degree of error. Despite all previous efforts, segmentation results often contain a considerable amount of error, leading to inaccuracies in the size distribution.

No significant attention has been given to the illumination of the images prior to segmentation. The purpose of illumination has been purely to provide sufficient light to capture a clear image of the particle. Illumination, however, plays a key role in the quality of images and we have exploited it further to enhance the performance of image segmentation. Through MFI, we used images captured with different illumination configurations to infer additional information about a scene.

3. MFI implementation

3.1. Original Algorithm

We illustrate how the MFI algorithm works by applying it to a simple single particle shown in Fig 1.

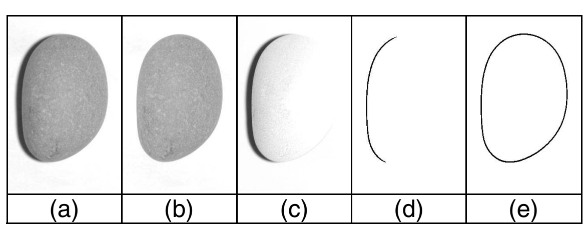

Figure 1 (a) Image taken with illumination from right (b) Max intensity image (c) Ratio image (d) Edge image (e) Combined edge image

Step 1)Image capture

Four images, I_n (n=1,2,3,4), are taken with the scene illuminated from different directions (Top, bottom, left and right). Fig 1a shows an image taken when the illumination is from the right and how the shadows are cast in the opposite direction.

Step 2) Max intensity image

Fig 1b shows the maximum intensity image computed by

$$I_{\max}(x) = \max(I_n(x)), n = 1,2,3,4$$

where $I_{max}(x)$ contains the highest intensity value amongst the four images for every pixel x and this has the effect of removing all the shadows. By distributing the light sources evenly around and close to the camera's centre of projection (COP) and ensuring uniform illumination, we can assume that $I_{max}(x)$ is a close estimation of having an image taken with a single light source at the camera's COP.

Step 3) Ratio images

Each of the four images is then divided by the maximum intensity image:

$$R_n(x) = \frac{I_n(x)}{I_{\max}(x)} \qquad for \qquad n = 1,2,3,4$$

Each pixel in the ratio image, $R_n(x)$ has a value of zero in shadowed regions and tends to unity in illuminated regions. The ratio image accentuates the shadows and suppresses the texture. The ratio image computed for the image taken in Fig 1a is shown in Fig 1c.

Step 4) Edge image

Applying an edge detector such as the Sobel operator on the ratio images produces an intensity gradient image. At an object's edge where a shadow starts, there would be a significant intensity change along the epi-polar ray originating from the light source. Pixels with significant intensity transitions from illuminated to shadowed regions are detected (Fig 1d). This eliminates false edges between the shadows and the background. Edge images are calculated for all four ratio images and the results combined to form a final image showing edges in all four directions. This is shown in Fig 1e.

3.2. Identification of fully visible particles

Due to the inherent limitation of 2D imaging in the visible spectrum, the image capture device is able to obtain a view only from the top of the scene. Underlying particles which are partially visible from the top would undeniably cause measurement errors if their partial visible surface area were taken to reflect the entire particle.

Thurley and Ng [13] address this problem through the use of 3D imaging. A surface topology of the scene is expressed in terms of 3D data through the use of a custom built active triangulation system utilizing a single CCD camera and projector. Fully visible particles can be identified by exploiting the additional depth dimension otherwise absent in 2D images. Thurley and Ng [13] reaffirms that 'Such a capability provides a significant advantage in the classification of fragments over photographic-based methods as it eliminates bias due to the treatment of partially visible fragments as if they were smaller entirely visible fragments.'

While MFI is not an entirely 3D technique, it does provide extra information beyond 2D techniques. Shadows can be used to infer information about the placement of objects in a scene, for example, identification of non-underlying particles. This is achieved through the use of a shadow map which is constructed by detecting pixels below a certain threshold amongst all the ratio images. Each region in the edge map is then uniquely labelled and the percentage of pixels identified as shadow pixels is calculated. A region with shadows beyond a certain threshold is likely to be a particle which is partially covered by other particles(s). This provides an extremely convenient and simple solution as compared to conventional 3D imaging.

Fig 2 shows how MFI can be used to identify fully visible particles automatically and the results were compared with visual inspection. Fully visible particles were isolated in an image using Photoshop which was used to verify the accuracy of MFI in automatically identifying fully visible particles. All the fully visible particles were identified by MFI, as shown in Fig 2c.

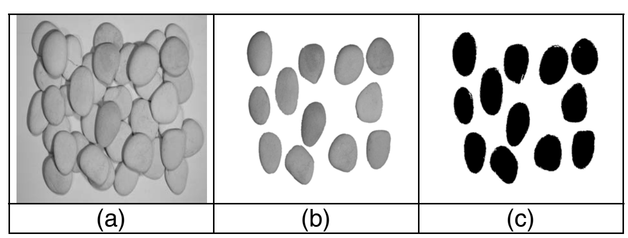

Figure 2 (a) Overlapping particles (b) Manual identification of fully visible particles (c) Automatic identification of fully visible particles using MFI

4. MFI evaluation

4.1. Evaluation method

Fig 3 shows a diagram of the setup used to implement MFI.

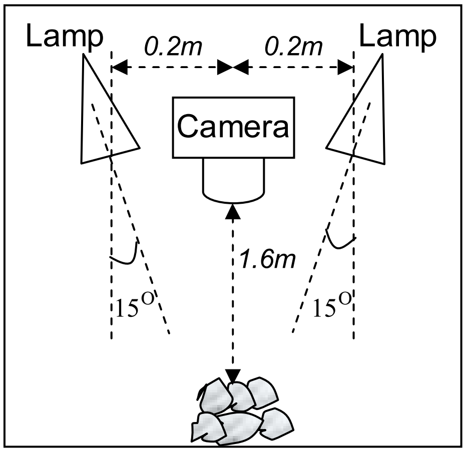

Figure 3 Experimental setup

A Nikon D100 digital SLR camera was used together with 300W incandescent lamps as illumination sources (instead of flashes as previously used in MFI). This did not affect the results obtained as the images were static. The focal length of the camera was 120mm and the resolution of the images was 1504 by 1000 pixels. A copy stand provided a highly configurable platform to mount the equipment on. Adjustable arms were used to secure the lamps around the camera to provide different illumination configurations.

In order to evaluate its performance, MFI was compared with two commonly used segmentation techniques, namely watershed and canny edge detection applied to the conventional (white light) image. Marker controlled watershed was used to reduce the problem of over-segmentation through automatic seed selection by morphological operations [5]. The canny edge detection was applied with a manual selection of low and high thresholds [5] which provided the best results. The aim was to measure results from MFI, watershed and canny edge detection against some gold standard. Researchers have often used mechanical sieving methods as the gold standard [7][8][11]. However, mechanical sieving introduces inherent measurement errors. There is a level of uncertainty as to whether the same particle would pass through the same sieve repeatedly in all of its orientations. Moreover, sieves often fix the bin size which causes inflexibility in examining non-standard size ranges.

Therefore, in our evaluation, mechanical sieving was not used as the gold standard for comparison. Instead, the size distribution calculated from images of physically separated particles placed on a contrasting background was used as the gold standard. All size distributions were based on equivalent spherical diameter, the diameter of a circle with the same area as the region within the particle's boundary in a 2D image. We define each region area as the total number of pixels in each bounded area of the segmented image. Image segmentation was performed on images taken from the top view where only the visible surface area of each particle can be captured. When the watershed and canny techniques were used, all regions within a realistic size range were considered as full particles and included in the size analysis. On the other hand, MFI allows size analysis to be performed only on fully visible particles. We used beach pebbles as representatives of particles in our evaluation. The pebbles were generally oval in shape and had smooth surfaces.

4.2. Evaluation results

Fig 4 shows the results of different segmentation techniques applied to a pile of pebbles.

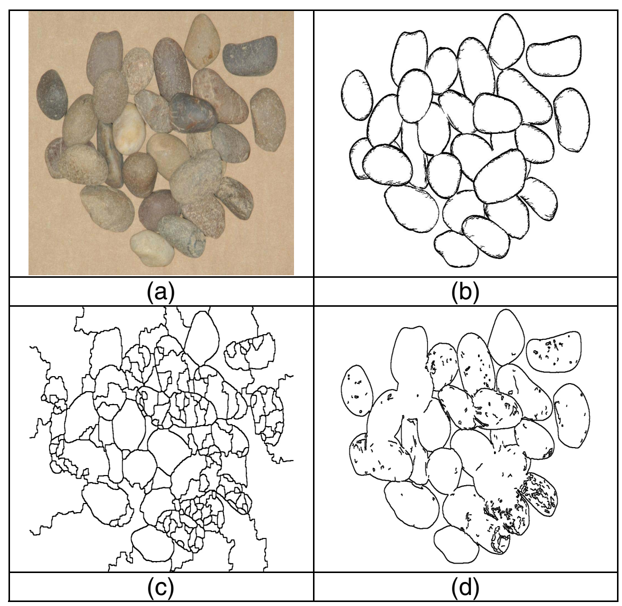

Figure 4 (a) Pile of particles (b) MFI edge map, (c) Watershed edge map (d) Canny edge map

Canny edge detection (Fig 4d) failed to identify many boundaries between overlapping particles. False edges were caused by texture variations present within the surfaces of the pebbles. While the watershed technique (Fig 4c) was able to produce complete boundaries, it faces the problem of over-segmentation where there is no way to ensure that regions represent true particles. Though edge gaps can still be seen in the results from MFI (Fig 4b), it outperforms both the watershed and canny techniques.

In order to quantify the difference in performance, we applied the 3 segmentation techniques on 230 pebbles. We repeated this process 10 times, randomly mixing the particles after each repetition. The results were combined and compared with the gold standard.

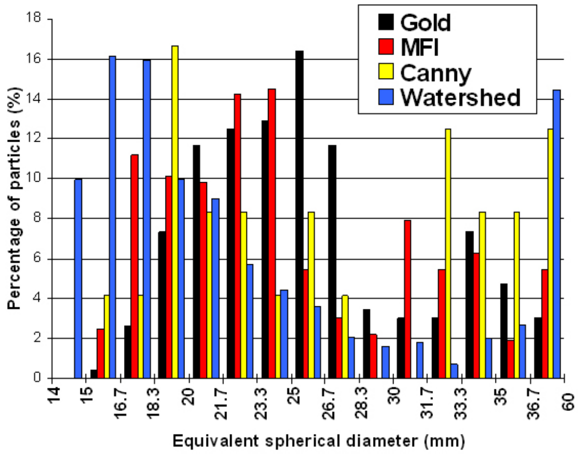

Figure 5 Size distribution of pebbles

Fig 5 shows the percentage of the total number of particles in different size bins. From the graph, one can observe that the size distribution of MFI most resembles the gold standard. For example, the gold standard indicates that 12.9% of the particles have an equivalent spherical diameter of between 23.3mm to 25mm. This is compared to 14.5%, 4.2% and 4.4% when the MFI, canny and watershed techniques were used respectively. Due to watershed's problem of over-segmentation, most of its regions were small, resulting in diameters falling in the lower ranges. Incomplete boundaries produced by the canny technique result in large regions, producing diameters in the higher ranges. The diameters in the lower ranges were likely to be caused by false edges within the surfaces of the particles. The average error across all bin sizes for the MFI, canny and watershed techniques compared to the gold standard are 3.5%, 5% and 7% respectively.

The quantitative analysis provided further evidence of the improvement in segmentation results using MFI. A main contributing factor to this improvement is MFI's unique ability to identify fully visible particles where many inappropriate regions such as underlying particles were eliminated.

5. Conclusion and future work

A novel technique in segmenting overlapping particles has been proposed. MFI shows great potential when compared with conventional segmentation techniques investigated. Despite best efforts, the watershed and canny techniques are limited by inherent constraints such as similar texture amongst overlapping particles. MFI has not only proved that illumination is a key factor in the performance of computer vision, but could also be used to enhance image segmentation and infer additional information about a scene. The ability to identify fully visible particles without the complexities of 3D imaging is valuable. MFI can be implemented easily with the addition of multiple illumination sources and computed in near real-time, making it a very practical solution. With a higher segmentation accuracy of particles, more precise size analysis can be achieved. It is assumed that the fully visible particles are a fair representation of the rest of the sample. The breakthroughs discovered in automated particle size analysis in this paper could be extended to a wider range of applications.

Further investigation will be carried out on increasing the robustness of the MFI technique on dynamic scenes and more complex particles.

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