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Granulometry using Mathematical Morphology and Motion

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Abstract

This paper describes an efficient framework for image-based granulometry, which provides three main contributions. First, unlike most of the existing work on particle delineation, which is based on the use of detected edges, our method–a region-based approach–relies on the use of mathematical morphology techniques. Second, we have explored the use of motion in order to recover the visible volume of the detected lumps through the recovery of dense disparity maps. Third, we have applied the proposed framework to the measurement of oil sand lumps, a problem not addressed in the literature of granulometry. The on-line analysis provided by the developed framework has been evaluated successfully on video streams. From the experimental results, we believe that the proposed framework can be applied efficiently to various real applications that are not limited to granulometry systems.

1 Introduction

Granulometry has been carried out in the past using tedious and laborious procedures such as sieving, centrifugation, and sedimentation. With the advent of inexpensive fast computing power, and the availability of inexpensive portable video cameras, image-based granulometry is becoming feasible. The advantages of using images over traditional sieving are as follows.

- Image processing does not interfere with or disrupt production.
- Image processing is relatively fast, allowing the analysis of many samples.
- Image processing is not affected by size of volumes of fragments.
- Image processing is a non-invasive procedure.
- The required equipment is easily affordable.

In the last 15 years, many image-based granulometry systems were developed at universities and by industry [4]. Their common goal was to compute the size distribution of fragments, and the information obtained has been used for many purposes, such as quality control, cost reduction, blast optimization, and fine-tuning of key parameters. Almost all developed approaches are based on edge detection whose methodology was developed in the 1970s. In [1], the authors present an edge-based approach to delineate particles. The developed approach is relatively complex, and uses segmentation techniques similar to those used in segmenting images of man-made objects. They applied their method to images of a lab rock pile. Other researchers have introduced techniques borrowed from the neural network field [2]. There are several commercial systems developed for the hard rock industry. However, estimating lump size distributions of oil sand is an open problem, and there is no published literature on the subject. There are many difficulties associated with oil sand lump analysis. Therefore, in addition to the classic difficulties associated with images of hard rocks, oil sand materials have different texture and reflecting properties from those of hard rocks. This makes the delineation procedure very challenging. Our experience shows that the gradient-based edges are not informative about the oil sand lumps. Thus, we have developed a region-based approach to delineate the oil sand lumps. The developed framework consists of two main features: (i) particle delineation using mathematical morphology, and (ii) volume recovery using motion. The overall structure of the proposed framework is illustrated in Figure 1. The source of images can be provided by a video camera or a digital video player playing a previously recorded video sequence featuring the conveyed oil sand material. In these images, one pixel resolution corresponds to 3.6 mm at the scene depth. The most related approach to ours is that of Fragscan system [7]. However, this system can measure only the maximum size of the lumps since it uses disks to perform numerical sieving. In contrast, our approach attempts to segment the image regions of the lumps using labelling techniques. Our method of particle delineation is able to measure the cross-sectional area of lumps which is richer than the maximum size.

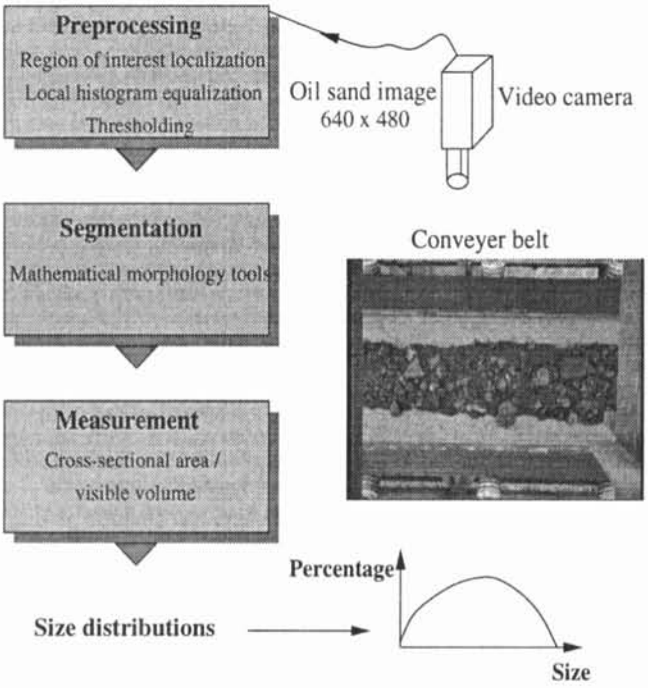


Figure 1: The main steps of the developed framework.

2 Particle delineation

The main steps of our delineation approach are: (i) the preprocessing stage, and (ii) the delineation stage, using mathematical morphology tools.

Preprocessing The main goal of the preprocessing stage is to transform the input image into a more suitable form. In this stage, three steps are taken. First, the oil sand materials are localized within the image. Second, the contrast of the obtained image is enhanced using local histogram equalization. Third, a binary image is produced with a thresholding operation. Ideally, particles have bright pixels and are surrounded by dark pixels (non particle). The binary image will be the input of the segmentation stage (see Figure 1).

Segmentation Once the binary image is obtained at the preprocessing stage, particle delineation will be performed using mathematical morphology tools. Each pixel in the binary image is either zero value, which indicates that the pixel does not belong to any lump (background or very dark region), or non-zero value, which indicates that the pixel belongs to a lump. Particle delineation can thus be carried out by labelling the connected non-zero pixels into distinct blocks. The binary image will undergo a series of operations, including: opening (an erosion followed by a dilation) with a 3×3 structuring element (or any other structuring element); removing isolated pixels; filling holes; and, eventually, connecting particle pixels into separate blocks using a 4-connectivity neighborhood [8]. Figure 2 displays the delineation results for a set of four typical images.

Metric measurement and size distribution In order to express the area of lumps in metric units, additional information is needed. In our case the scaling factor can be easily recovered since the width and height of our conveyer belt are known. Note that there are many ways to express the lump size. We have adopted the diameter of an equivalent circle.

Fusion & disintegration Some detected blocks do not correspond to the physical lumps. In other words, a single block may correspond to more than one lump (typically, two lumps). This is referred to as the problem of fusion. On the other hand, more than one block may result from the same lump. This is referred to as the problem of disintegration. Disintegration tends to introduce a bias towards small sizes. However, small lumps cannot be measured with high accuracy due to digitization and algorithm limitations. The fusion problem can be alleviated by using an opening operation with a fixed structuring element. A large proportion of merged lumps consists of blocks joined by an isthmus. It is well known that opening can break such isthmuses (see [3], [8]).

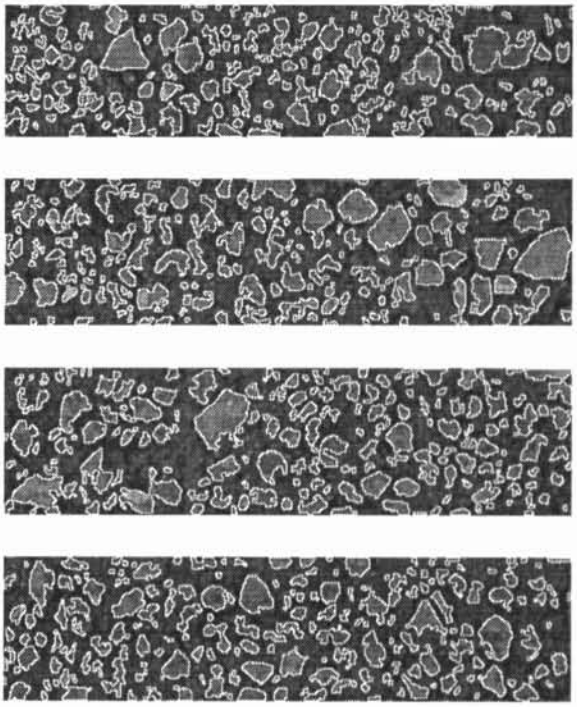


Figure 2: Oil sand lump delineation using our segmentation method (four images).

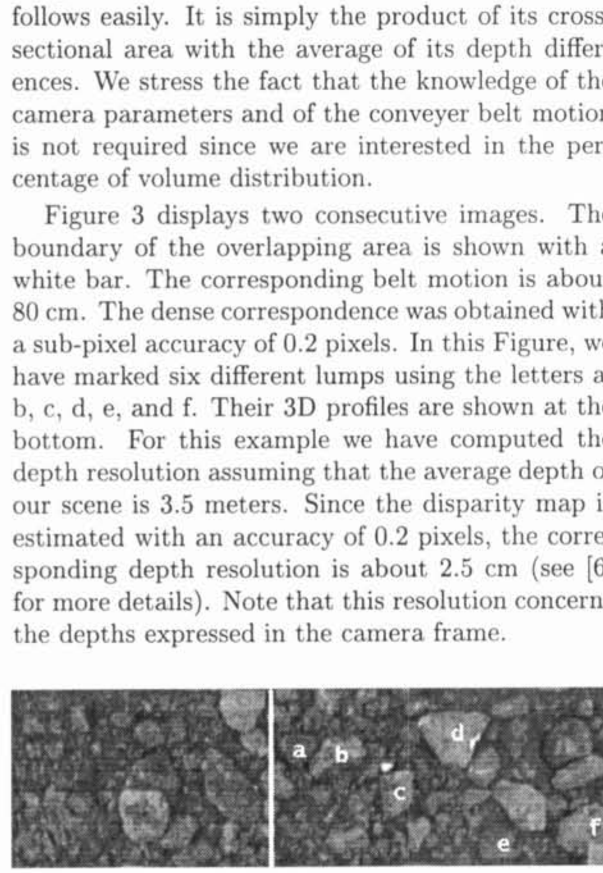
3 Volume recovery

The direct recovery of volume information has not been addressed in the literature of granulometry. Existing work for volume recovery does not perform a direct measurement. More precisely, these methods rely on the use of geometric probability. Two kinds of methods have been used to recover the volume using this scheme. The first kind of approaches assumes that the lumps being analyzed have a simple shape (e.g., a sphere or an ellipsoid). Thus, recovering the volume becomes very simple, since the cross-sectional area is known. The second kind of approaches attempts to construct an unfolding function that can be used to transform cross-sectional area distributions into volumetric distributions [5]. It is worthwhile noting that these methods perform well if and only if the actual 3D shape of the lumps fits well with the made assumption (for the first kind), and the unfolding function is accurately estimated (for the second kind). Therefore, it seems that a direct measurement will provide more accurate results, especially for fragments whose shape is irregular.

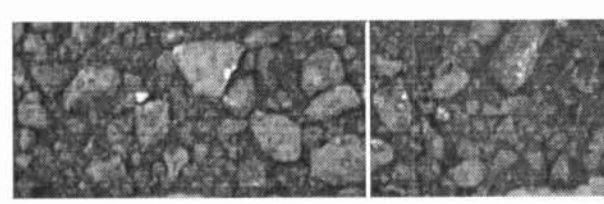
Since the image stream is already available and since the belt motion is constrained, we have adopted the strategy of 3D structure from motion or 3D structure from stereo which has been a central problem in computer vision for the last two decades. It has been demonstrated that motion (camera motion or scene motion) can provide rich information about the 3D structure of the viewed scenes. Using such techniques, the 3D structure can be recovered once the correspondence problem is solved. However, in the literature of computer vision, much work has been done to recover the 3D structure of a sparse set of features, whereas relatively little work has been done on recovery of volumetric description.

Specifically, we have exploited the two facts: (i) the conveyer belt motion is constrained to belong to a fronto-parallel plane, and (ii) the depth variation of the analyzed scene is small compared to the absolute depth. Note that if two images are taken within a fixed interval of time, they can be considered as a stereo pair whose baseline is equal to the performed conveyer belt motion. Our strategy is summarized as follows. At any time we grab two images that have a significant overlapping area. First, the 2D global alignment is recovered by minimizing a global SSD measurement (this is done once for all assuming that the interval time is constant and the conveyer belt moves at a constant velocity). Second, a dense disparity map is built between the two consecutive images using normalized cross-correlation. In this process, the 2D global alignment is used to locate the search windows in the second image. Third, the dense depth map is then converted into a scaled dense depth map. Once the depth profile of each lump is recovered, the visible volume of each lump follows easily. It is simply the product of its cross-sectional area with the average of its depth differences. We stress the fact that the knowledge of the camera parameters and of the conveyer belt motion is not required since we are interested in the percentage of volume distribution.

Figure 3 displays two consecutive images. The boundary of the overlapping area is shown with a white bar. The corresponding belt motion is about 80 cm. The dense correspondence was obtained with a sub-pixel accuracy of 0.2 pixels. In this Figure, we have marked six different lumps using the letters a, b, c, d, e, and f. Their 3D profiles are shown at the bottom. For this example we have computed the depth resolution assuming that the average depth of our scene is 3.5 meters. Since the disparity map is estimated with an accuracy of 0.2 pixels, the corresponding depth resolution is about 2.5 cm (see [6] for more details). Note that this resolution concerns the depths expressed in the camera frame.



First image of the stereo pair



Second image of the stereo pair

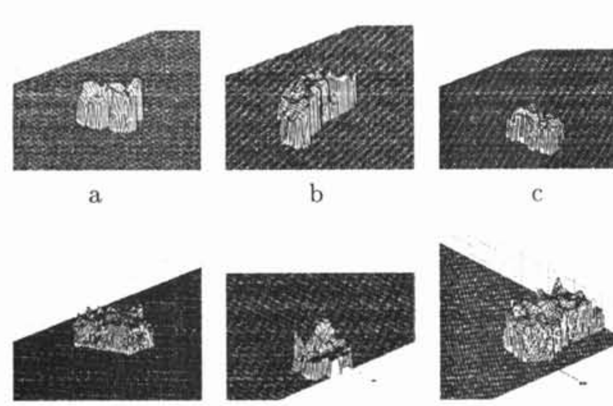


Figure 3: Two typical consecutive images. The boundary of the overlapping area is shown with a white bar. The bottom displays the 3D profile of six lumps marked with the letters a, b, c, d, e, and f.

4 Experimental results

Syncrude Canada provided us with a one-hour video tape. This video was captured with a camera pointing downwards towards the conveyer belt that carries the oil sand materials. The framework described in this paper (particle delineation and volume recovery) has been implemented using a mix of Matlab and C languages. The data were analyzed on a non-dedicated Celeron 500 MHz PC running Linux using the frame grabber WinTV. Analysis of the cross-sectional areas runs at 2.5 Hz, i.e., it takes 0.4 s per image. Analysis of both the cross-sectional areas and volumes runs at 1.2 Hz, i.e., it takes 0.85 s per stereo pair. Note that these times include the image capturing. Thus, both cross-sectional areas' distribution and volume distribution are computed on line, i.e., they are produced almost at the same time of image capturing. Figure 4 shows the cross-sectional areas' distribution associated with 6000 images that correspond to 12 kilometers of transported materials.

Figure 5 shows the volume distribution associated with 2000 stereo pairs.

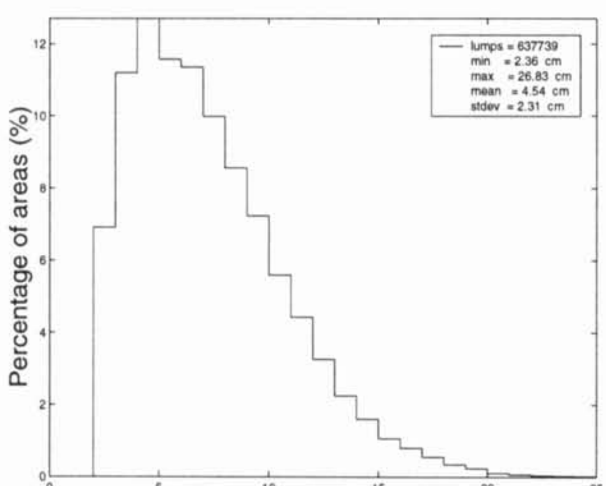


Figure 4: Cross-sectional areas distribution associated with 6000 images.

5 Conclusion

In this paper, we have presented an efficient framework for image-based granulometry. This framework has been used to measure oil sand lumps, a problem not addressed in the literature of granulometry. The developed framework consists of two main features: (i) particle delineation using mathematical morphology, and (ii) volume recovery using motion. To the best of our knowledge, our proposed method is the first attempt used in granulometry to recover volume from optical images through dense disparity maps. Existing methods rely on geometric probability whose efficiency is very limited. From the experimental results and the on-line analysis, we believe the proposed framework (particle delineation and volume recovery) can be applied efficiently to various real applications.

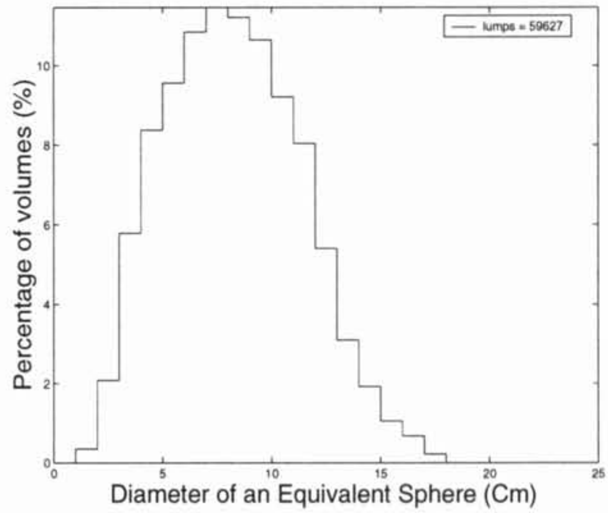


Figure 5: Volume distribution associated with 2000 stereo pairs.

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