

## Separating touching and overlapping objects in particle images – A combined approach

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Determination of particle size distribution by image analysis is often rendered ineffective due to the presence of touching and overlapping particles in the acquired images. The size and shape estimation done on the image without separating the touching and overlapping objects lead to gross errors in estimated values of size and shape. The existing methods of separation like watershed segmentation and morphological processing suffer from problems like over segmentation and relatively large processing times. A new automatic algorithm to separate the touching and overlapping particles based on the intensity variations in the regions of touching and overlapping particles and geometric features of boundary curves is developed. The performance of the algorithm is compared with that of the watershed segmentation algorithm as well as visual examination of images.

### 1. Introduction

Online measurement of particle size distribution (PSD) can be of utmost importance in the monitoring and control of many particulate processes in the pharmaceutical and fine chemicals industries amongst others. However many techniques of direct measurement are not suitable for in-situ/online characterization purposes. Direct real-time visual characterization is a promising alternative to complex and expensive particle measurement systems and attempts in this direction have been reported in literature (Nazar et al. (1996), Watano and Miyanami (1995)). However, this field still needs research and development particularly in overcoming the problem of touching and overlapping particles.

There always exists touching and/or overlapping particles in images taken from particulate systems where no particle dispersion is applied prior to image capture. There are processes that are not amenable to dispersion, those of fragile nature like flocs and certain crystalline particles. Development of an algorithm which can address issue of touching/overlapping objects is the concern of the present paper. The existing approaches invariably take a priori knowledge about the shape of the particles as input (Honakanen et al. 2005; Shen et al. 2000). Such an assumption does not hold good for many real life industrial systems. The approach adopted in this paper is based on capturing the intensity variations along the regions of touch/overlap and using this information to separate such particle aggregates. Wherever intensity variation information alone is not conclusive enough to identify such regions, we use geometric features of boundary curves as complementary information.

## 2. Methods and analyses

The major steps involved in processing of an image are preprocessing, segmentation and feature extraction. Though many image processing methodologies exist for each of these stages, the selection of appropriate methods suitable for the particular genre of images is very important for achieving best results. We next discuss some details of these steps including preprocessing, capturing of intensity variations, binarizing, extraction of geometric features of boundary curves and separation of the touching and overlapping regions.

### 2.1 Preprocessing

Median filtering is done on the image with a kernel size of  $[3 \times 3]$  to remove random noise. This filter is an order statistic filter which replaces the value of a pixel by the median of the pixel values in a small neighborhood (Gonzalez and Woods, 2002):

$$f(x,y) = \text{median}\{g(u,v)\} \quad (1)$$

where  $(u, v) \in S(x,y)$  the neighborhood around  $(x,y)$ . Fig. 1 shows the original image after median filtering.

### 2.2 Segmentation

Once the image is denoised, identification of objects has to be done and this process is in general known as segmentation. A large number of segmentation techniques are present in the literature (Pal and Pal, 1993) but in the images of particulate systems, the objects (particles) and background differ distinctly in terms of the brightness value. So we can separate the objects from background by thresholding which is the process in which a criterion based on pixel intensity value is used.

#### 2.2.1 Thresholding

We here use Otsu's method of global thresholding based on image histogram (Otsu, 1979). In this method the pixels are divided into two classes such that the mean of each class is as separated as possible and the variance within each class is as least as possible and class boundary is the threshold value. The gray scale image ( $I_g$ ) and the binary image ( $I_{bw}$ ) can be represented by the following equations

$$I_g = \{x \mid 0 \leq x \leq U\}; \quad I_{bw} = \{x \mid x \in (0,1)\} \quad (2)$$

where  $U$  is the upper limit of the intensity which has a value of 255 for a grayscale image. The binarized image is shown in Fig. 2. It can be seen that most of the touching regions are accounted for as belonging to the object regions (white) resulting in a single large particle in the center of the image. Feature extraction based on such incompletely segmented image will produce erroneous results. The traditional method of watershed segmentation (Russ,

2002) for touching/overlapping objects suffers from severe over segmentation when objects are not of regular shapes. The following sections describe the proposed new algorithm.

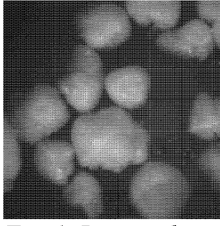


Fig. 1. Denoised gray scale image.

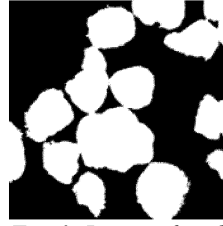


Fig. 2. Image after thresholding

### 2.2.2 Capturing the dip in intensity across touching and overlapping regions

The touching and overlapping regions have intensity variations characterized by local dips in intensity values on account of the relatively less light being reflected from these regions compared to other areas of the particulate objects. The graph on the right in Fig. 3 shows variation of intensity along the horizontal line in the gray scale image in the same Fig. on the left. The intensity dip at a touching region is marked with an oval.

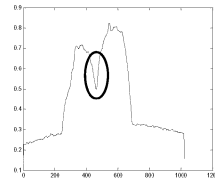
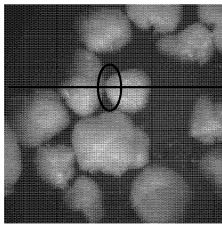


Fig. 3. Intensity variation along a horizontal line.

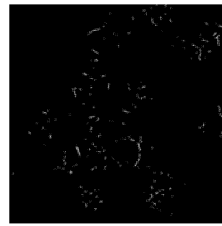


Fig. 4. Computed dip line.

The most obvious and common method to identify these regions is by calculating the gradient (Canny, 1986). However, the intensity change at many of these dips is not very rapid and would not have an appreciable value for the absolute gradient. Hence instead of gradient calculation, we identify bottom points of above mentioned dips by scanning the image pixels in various directions. Collection of such points forms what we call a 'dip line' which identifies a touching or overlapping region. We are not interested in gradual changes in the background area and hence dip points contained only in the object area are retained. The dip lines thus captured are shown in Fig. 4. Morphological dilation is done to bridge small gaps due to random noise in an otherwise continuous line. Utilization of these dip lines for separation of touching and overlapping particles is described in a later section.

### 2.2.3 Extracting geometric features of boundary curves

Another key feature of touching/overlapping regions is existence of sharp turns (concavity) in the vicinity of intersection or tangency of the boundaries of two objects. Moreover, the wedges formed on both sides of a touch/overlap is oriented in opposite direction. Several

methods have been reported in literature (Shen et al., 2000; van den Berg et al., 2002) for quantifying the magnitude and orientation of the ‘concavity’ or ‘wedgeness’ of boundary curves and we are using the concept of center of gravity (COG) and local eccentricity here. In this method, for a particular pixel on the boundary the coordinates of COG is calculated by the following formulae:

$$X_{cog} = \frac{1}{N} \sum_{i=1}^N x_i ; \quad Y_{cog} = \frac{1}{N} \sum_{i=1}^N y_i \quad (3)$$

where  $x_i$  and  $y_i$  are relative coordinates of the  $N$  neighboring points (also lying on the boundary) with respect to the particular pixel  $i$ . Then the eccentricity is calculated as

$$\mathcal{E} = \sqrt{X_{cog}^2 + Y_{cog}^2} \quad (4)$$

The orientation vector of COG relative to the pixel under consideration is represented by its coordinates  $(X_{cog}, Y_{cog})$ . The magnitude of eccentricity and orientation vector of the wedge point are used (wherever necessary) in conjunction with dip lines to provide a robust separation methodology for touching and overlapping objects as discussed in the next section.

#### 2.2.4 Separation of the touching and overlapping particles

To achieve separation of touching/overlapping particles, we further process the threshold image with the additional information of dip lines. The image of dip lines in Fig. 4 is subtracted from the binary image (Fig. 2) and the result is shown in Fig. 5. Separation has been achieved at many touching regions. But we have black pixels on the object body as well corresponding to dip lines entirely contained in the objects. To decide whether a dip line represents a minimum at touching/overlap region, we propose the following logic: wherever particles are touching or overlapping, the dip line starts from the boundary. The reasoning behind this is that the intensity variation is more prominent where the boundaries of particles cross. Based on this reasoning, we exclude all dip lines which are not extending up to the boundary of the objects. The resulting picture is shown in Fig. 6. It can be seen that apart from dip lines which completely separate touching/overlapping regions, we have dip lines which start from boundary and running into the object body but failing to reach the boundary curve on opposite side so that a complete separation is achieved. We refer to these kinds of dip lines henceforth as ‘burrows’. Among these burrows we can identify different kinds - some are of very short length, while others form a pair seemingly coming from a continuous line broken by some noise, yet others run very deep into objects and almost extend to boundaries on opposite sides but just stop short of piercing through. Ignoring the burrows which are very short in length, we utilize the two latter categories of burrows in conjunction with the geometric features obtained by methods explained in section 2.2.3. The close tips of a pair of burrows are joined if the following two conditions of boundary curve geometry are satisfied: i) the pixels on the boundary curve in the vicinity of the starting point of the burrow (on the boundary) has a considerable value for the eccentricity and ii)

the orientation vectors at the start of each burrow in the pair have opposite orientation. The result of such a joining is shown in Fig. 7 (marked by an oval). There is no second category of unpaired burrows in this particular image. However, in such cases the distance between the nearest point of high eccentricity on the boundary and the tip of the burrow is calculated first. If this distance is small enough (less than a threshold) then the orientation checks are done as before and the burrow tip is connected to the boundary point on opposite side completing the separation.

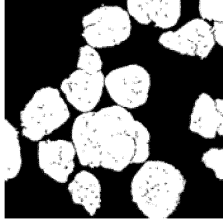


Fig. 5. Binary image with dip lines.

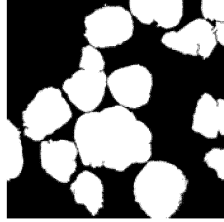


Fig. 6. Image after dip line processing.

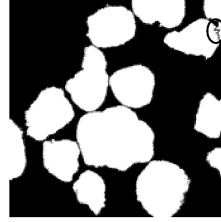


Fig. 7. After joining burrow tips.

### 3. Results and Discussion

Once the touching and overlapping objects are separated, individual objects are labeled and size feature is determined. The feature used to represent the size is the equivalent diameter which is the diameter of the circle of equivalent area as the object. The comparison of PSD of the objects in Fig. 1 before and after application of separation algorithm is given in Figs 8 and 9.

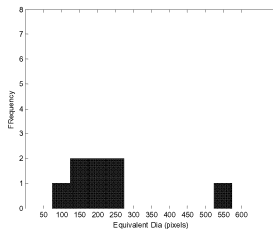


Fig. 8. PSD of non-separated objects in Fig. 1.

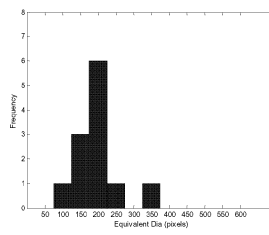


Fig. 9. PSD after application of algorithm.

The effect of touching/overlapping on the PSD is clearly evident in this comparison where the PSD of the image with no separation is biased towards higher sizes as expected due to the agglomeration of image object. Further our results are compared against traditional watershed segmentation technique results (Figs 10-11). It can be seen that watershed method suffers from over segmentation and hence a large number of small particles are generated and evident in the PSD of Fig. 11. Our method shows superior and far less error in separation compared to traditional watershed segmentation technique.

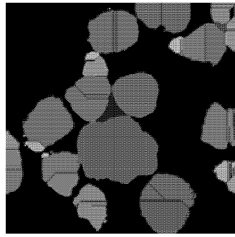


Fig. 10. Result under watershed segmentation.

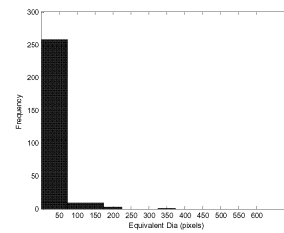


Fig. 11. PSD under watershed segmentation.

#### 4. Conclusions and future work

A combined approach based on intensity variations and geometric features of boundary curve is proposed to achieve separation of touching and overlapping objects in images of particulate systems. Instead of normal approach of gradient calculation to identify characteristic variations in intensity, trapping of local dips in intensity along regions of touch/overlap was effectively employed. Wherever the information from intensity variation was not complete, geometric features of boundary curve was used as complementary information to complete the separation. Multi-resolution analyses are currently being pursued to improve the effectiveness of capturing the intensity dips so that loss of intensity variation information can be curtailed.

#### 5. References

- Canny, J., 1986, A Computational approach to edge-detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 8, 679-698
- Gonzalez, R.C. and R.E. Woods, 2002. Digital Image Processing, Prentice Hall.
- Honakanen, M., P. Saarenrinne, T. Stoor and J. Niinimäki, 2005, Recognition of highly overlapping ellipse-like bubble images. Measurement Science and Technology, 16, 1760-1770.
- Nazar A.M., F.A. Silva and J.J. Ammann, 1996, Image Processing For Particle Characterization. Materials Characterization, 36, 165-173.
- Otsu, N., 1979, A threshold selection method from gray level histogram. IEEE Transactions on Systems Man and Cybernetics, 9, 62-66.
- Pal N. R. and S.K. Pal, 1993, A review of image segmentation techniques. Pattern Recognition, 26, 1277-1294.
- Russ, J.C., 2002. The Image Processing Handbook, CRC Press.
- Shen, L., X. Song, M. Iguchi and F. Yamamoto, 2000, A Method for Recognizing Particle in overlapped Particle Images. Pattern Recognition Letters, 21, 21-30.
- van den Berg EH, A.G.C.A. Meesters, J.A.M. Kenter and W. Schlager, 2002, Automated separation of touching grains in digital images of thin sections, Computers and Geosciences, 28, 179-190.
- Watano, S. and K. Miyanami, 1995, Image Processing for on-line monitoring of granule size distribution and shape in Fluidized bed granulation. Powder Technology, 83, 55 -60.