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An efficiency improved recognition algorithm for highly overlapping ellipses: Application to dense bubbly flows

Mathieu de Langlard[a], Hania Al-Saddik[a], Sophie Charton[a], Johan Debayle[b], Fabrice Lamadie[a,*]

[a] CEA/DEN/DMRC/SA2I, Bagnols-sur-Cèze F-30207, France
[b] Ecole Nationale Supérieure des Mines, SPIN/LGF UMR CNRS 5307, Saint-Étienne, France

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A B S T R A C T

Image analysis is a widespread and performant tool for the characterization of particulate systems in chemical engineering. However, for bubbly flows, due to the wide range of particles size, shape and the appearance of large clusters resulting from particles projections overlapping at high hold-up, automatic particle detection remains a challenge. An efficient methodology for bubbly flow characterization based on pattern recognition is presented. The proposed algorithm provides an exhaustive, robust and computationally efficient way of analyzing complex images involving large ellipse clusters even in concentrated medium. The method is fully automated. A sub-clustering approach enables significant computation time reduction. Moreover, thanks to its ease of parallelization, it allows considering real time monitoring.

1. Introduction

Image analysis has become a powerful tool for monitoring particulate systems as the ones encountered in chemical processes, using information extracted from a 2D orthogonal projection of a population of 3D particles [1–3]. The term *particles* is used in this context to designate specifically either bubbles or droplets. Although the experimental part is rather simple and consists of a limited number of set-ups, the image processing methods are many and various. Since the popular Hough transform circle detection [4] and its extension to ellipses detection [5,6], whose application range is usually far from the particulate systems encountered in industrial processes, a lot of studies have been dedicated to the improvement of image processing algorithms. However, the still more or less manual detection of the 2D orthogonal projection of the particles, and the lack of automatic suitable approaches in the case of dense populations, are among the main remaining challenges to be addressed. While promising algorithms are currently emerging to enable fully automatic particle characterization [7,8], robustness issues still arise when large aggregates of 2D projection of particles are involved. These clusters are indeed very difficult to analyze and specific approaches are necessary. In basic algorithms, these clusters are ignored based on constraint conditions such as sphericity or convexity index. Classical image analysis reasoning does indeed consider that 2D projection of the particles within clusters occurs as a non-selective process and that ignoring these clusters would not bias the measurement. However, large projections of particles are more likely to be present in clusters rather than as individual entities [9]. Thus, ignoring clusters in the measurement would bias the analysis.

There are two major classes of methods for pattern recognition on a 2D image: the non-parametric techniques such as the morphological watershed transform, and the parametric techniques, like the Hough transform or other direct object fitting algorithms. Here, the term *object* refers a 2D bounded set in the Euclidean plane. Lau et al. [10] used the classical watershed transform to determine the particle size distribution (PSD) in dense particle flows. However the objects were assumed to be circular, which is likely to induce a shift of the PSD towards the large particles size and an apparent overestimation of the number of detected particles caused by the processing itself. Still considering the watershed transform, Karn et al. [7] separated the in-focus particles from the out-of-focus ones, which are extracted by using morphological operations, and treated each population independently. This methodology reduces the risk of over-segmentation frequently encoun-

* Corresponding author.
E-mail addresses: fabrice.lamadie@cea.fr, lamadie@free.fr (F. Lamadie).

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tered with the watershed transform [11]. Farhan et al. [12] used an alternative non-parametric approach. They detected split lines in a clump of 2D convex objects and iterate to refine these split lines using the image intensity. Their technique proved to be efficient and gave satisfactory results in situations where particles touch but do not overlap. While this is the case for the microscopy images of human cells they studied, this situation is rarely encountered in typical chemical engineering applications. Recently, a hybrid approach has been suggested by Fu and Liu [1]. The authors used the benefits of three well known segmentation methods: the watershed transform, the skeleton image and an adaptive threshold [13]. By coupling these techniques, one compensate for the drawbacks of each of the 3 methods used separately for segmentation. Based on several examples of individualization of objects within a cluster, satisfactory agreement was additionally assessed by the authors. Many examples of parametric processing methods applied to the detection of particles projections are also related in the literature. For their study of emulsification kinetics, Khalil et al. [14] assumed that the droplets were spherical and they investigated the time-evolution of the PSD using the famous Hough transform developed by Illingworth and Kittler [4]. However, this method failed when too many projections of particles overlap, even if the generalized Hough transform is used. For their study of bubbly flows, Honkanen et al. [15] proposed an original algorithm to detect overlapping ellipses corresponding to the 2D orthogonal projections of ellipsoidal bubbles in a dense population. In this approach, the boundary of the particles cluster is first detected. Then the points of the boundary that represent the connecting points of overlapping objects (subsequently referred to as concavity points) are found. The sections of the edge delimited by the connecting points and belonging to the same object are grouped. At last an ellipse is fitted on each cluster of edge segments. However, the method used for grouping the edge segments is not fully robust and often leads to incorrect detection even in the case of small clumps of objects. More recently, an improved method was proposed by Zhang et al. [16]. It consists of grouping the segments according to an average distance deviation criterion (called ADD) between the fitted ellipse, on one hand, and the corresponding group of segments in the image on the other hand. However, instead of solving the global minimization problem according to the merit function ADD, the authors proposed to group the segments according to 3 constraints. While the technique described by Zhang et al. [16] provides a significant improvement for the detection of ellipses in a clump of objects (*e.g.* compared to Honkanen et al. [15] and Shen et al. [17], the constraints imposed are empirical and must be adjusted for each new configuration of overlapping ellipses. An alternative approach based on seed points extraction and fast radial symmetry transform has been recently proposed by Zafari et al. [18] for the segmentation of overlapping elliptical objects in poor quality images. Although the method is robust and fast, it is strongly dependent on the performance of the seed points extraction.

Hence, among the available image processing techniques, none of them are really suitable for fast and/or efficient detection of overlapping, and possibly non-spherical particles, such as the ones prevailing in images typical of the dense bubbly flow encounters in many industrial applications. In this study, using the ADD criteria brought out by Zhang et al. [16], we describe a fully automated method for grouping the edge segments which is both efficient in terms of ellipses detection, and from a computational point of view, by offering interesting parallelization potential to speed-up the calculation, thus enabling online monitoring.

2. The proposed method

In this section, the main steps to achieve ellipse cluster decomposition in a binary image are described. The prior transformation of gray level images into suitable binary images is treated in Section 3.2. Starting from a binary image, the pattern recognition process consists of the following successive steps: i) identification of all the Region of Interest (RoI) - note that a RoI can be an isolated ellipse as well as a cluster of ellipses -, ii) extraction of the edge of the whole RoI, iii) splitting the edge into segments separated by connecting points, iv) grouping the segments, v) fitting an ellipse on each group of segment, vi) candidate ellipses evaluation and bad candidates rejection.

2.1. Detection of edge segments

Identification of RoI in a 2D binary image and subsequent contour extraction is classical in image processing, and will not be detailed further [19]. Segment detection along the contour is achieved through the detection of what is called "connecting points" [15], *i.e.* the positions of local minima of the curvature function along the boundary. The curvature of a 2D set boundary exists if the arc boundary of the regarded set is twice differentiable with continous second derivative. Methods to compute the curvature of a boundary set on a 2D image can be found in [20]. These connecting points can therefore be interpreted as concavity points, which will be used by the detection algorithm.

Here, the detection method proposed by Farhan et al. [12] is used. A straight line segment of user-defined length connecting two points of the contour is moved along the boundary. As long as the straight line segment is totally enclosed in the cluster (in green in Fig. 1), the convexity of the boundary between the two contour points is guaranteed. Otherwise (in red in Fig. 1), there exists at least one concavity point in this particular part of the contour. The exact location corresponds to the maximum of the Euclidean distance between the considered contour segment and the probe line. Then, only one concavity point can be detected when the convexity condition is violated. The process, illustrated in Fig. 1a, is repeated until the boundary is totally swept. Note that the length of the straight line segment has to be adapted in order to minimize the number of missed concavity points, as shown in Fig. 1b.

Practically speaking, the construction of the line segment is as followed. Pick up a pixel of the contour. The line joining this pixel and the one of the contour located at 25 pixels away is the straight line segment. In this way, its length is changing depending on the curvature of the arc of the contour that defines it. This construction is robust as it can fit to the shape of any cluster of objects. It has been observed through experiments that such a distance - fixed here at 25 - between the extremities of the line segment gives satisfactory results. Moreover, slightly changing this value (*e.g.* ± 10 pixels) does not really affect the detection of the concavity points. There are two ways of defining the step size when the straight line segment is moved along the contour. If the convexity criterion is satisfied, the third adjacent point to the previous *first* extremity of the straight line segment is taken as the initial point. Otherwise, the third adjacent point to the previous *second* extremity of the line segment is chosen.

Following the detection of concavity points, the contour is divided into n segments (where n is the number of concavity points). Each segment is assumed to belong to at least one ellipse embedded in the cluster, and an ellipse can potentially include several segments. As a consequence, it is mandatory to find the best combination of the n segments into p ellipses in order to extract the most probable cluster decomposition. It is worth noting that other methods for detecting these concavity points have been proposed in the literature such as the detection of local minima in the curvature function [15,20,21], a breakpoints detection by rotating curve [17] or a polygonal approximation technique used by Zhang et al. [16]. The technique adopted in this paper has the merit to be fast, robust and easy to implement.