Particles detection in a 2D-image of overlapping crystals based on community detection

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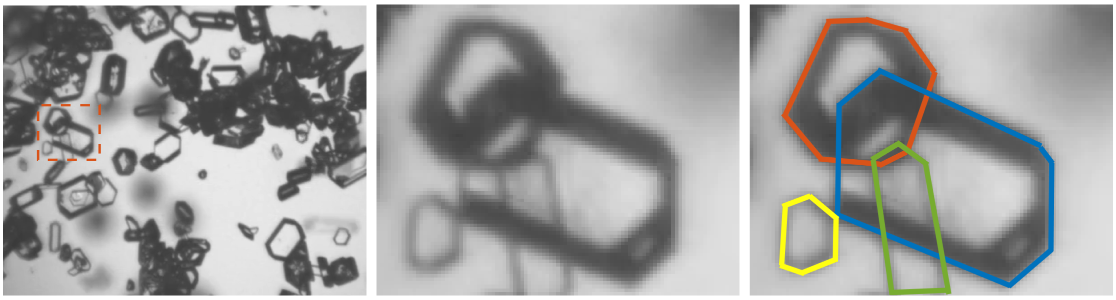
Abstract



(a) Example of an image (b) A cropped aggregate (c) Identified crystals

Figure 1: An image of Adipic acid crystals and the cropping windows (a), a crop of an aggregate of crystals (b) and its hand made individualization (c).

This work is motivated by the control of industrial crystallisation processes, which involve the knowledge of the crystals distribution over time. For this purpose, an in situ camera in batch crystallisers provide 2D images of the projected crystals population in real time such as Figure 1 (a).In order to characterize the geometry of the overlapped crystals, advanced image processing [1, 2] or stochastic geometry [3] can be used.
The proposed approach in this study is based on community detection (as done in social networks [4]). One can see on the images that the borders of individual crystals is quite visible and such a data Figure 1(b) looks like a tessellation of the union of crystals. Indeed, for instance in Figure 1 (b-c), four polygonal crystals are recognizable from a human visual perception (Gestalt theory [5]). It involves the use of topological and geometrical relationship between tessellation cells to make the decision to put the cells in the same crystal or not. Our objective is to provide an automatic detection of the crystals based on such ”community membership” rules.

Formally, one consider a 2D random aggregate A defined as a union of a familly $\mathcal{F}$ of 2D convex sets $\mathcal{F} = \{X_1, \cdots X_n\}$ centred on random position $x := (x_i)_{1 \leq i \leq n}$ as $A = \bigcup_{i=1}^{n} x_i + X_i$ and assume that the random vector of position x has a probability density (this technical condition will be discussed later).
Let $T = \{S_1, \cdots S_N\}$ a tessellation of A which is thinner than the minimal tessellation showing the borders of the convex sets X_i (defined as the tessellation of the aggregate A engendered by the X_i with the intersection and the set difference operators). For such a tessellation T, for any X_i there is a subset of T which is a tessellation of X_i, i.e. for any X_i there is $T_i \subset T$ such that $X_i = \bigcup_{S_j \in T_i} S_j$ (Figure 2 (a)).
We try to get the reconstruction of the full family $\mathcal{F} = \{X_1, \cdots X_n\}$ from the available information on the cells S_k of the tessellation T. Obviously for a given aggregate A and its

tessellation T there is several candidates for the family $\mathcal{F}$. However some considerations allows us to almost surely uniquely define the reconstruction, considering the randomness of A (the fact that x has a density) and the knowledge of the weights of the cells defined as $w(S_i) = \#\{X_k \mid S_i \in T_k\}$.
The geometrical combinatorial problem presented above can be modeled by a graph (Figure 2) and reformulated as a community detection problem, as done in social networks [4]. Indeed, considering that the tessellation cells are the vertices of the graph provided by topological and geometrical relationship on its edges, the convex sets X_i can be seen as communities to find.
We propose an algorithm of detection based on maximal clique detection on our graph provided by the edge relation $\mathcal{R}$ defined as $S_i \mathcal{R} S_j \Leftrightarrow ConvHull(S_i \cup S_j) \subset A$. Notice that for this relation a particle X_i is always a clique (complete subgraph) of the graph (Figure 2 (b)), which is always included in a maximal clique of the graph. The use of such a property (and the particle convexity) with the weights information allows us to identify the particles X_i from the cliques using an iterative algorithm.

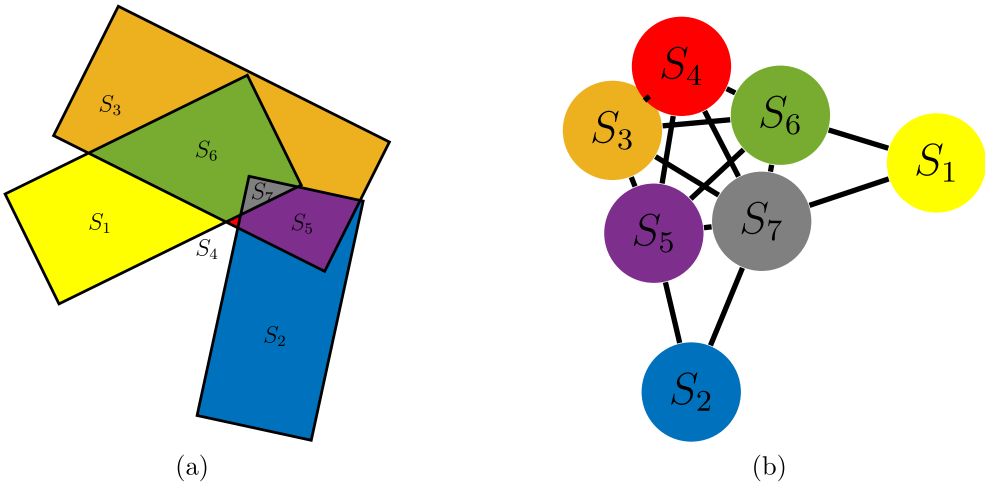


Figure 2: An aggregate of three rectangle and its minimal tessellation (a). The corresponding graph provided by the convex hull relationship on its edges $\mathcal{R}$ (b).

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