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## Active colloids segmentation and tracking

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#### ABSTRACT

Active colloids constitute a novel class of materials which have drawn a lot of attention in recent years. They are composed of spherical metal particles converting chemical energy into motility, mimicking micro-organisms. Understanding their collective behavior is key to applications. In this context, we address the problem of segmenting and tracking colloids in long video sequences corrupted with severe illumination changes. We propose a very accurate method to recover the individual trajectory of each colloid. First, a region-adaptive level set method is used to segment individual colloids or small clusters. Combining with the circular Hough transform further refines the segmentation. Second, we recover simultaneously all the colloids' trajectories using a modified min-cost/max flow method on a weighted graph with colloids as vertices. No motion regularity is assumed to define graph edges and their cost. The proposed method is evaluated on a real benchmark composed of nine video sequences with annotations. In terms of CLEAR MOT metric – a standard metric for evaluating multiple target tracking algorithms – our approach outperforms very significantly four standard methods.

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#### 1. Introduction

The modeling of dense active suspensions of artificial selfpropelled colloids has recently aroused the interest of physicists [1,2]. Typically, colloids are gold spheres half covered with platinum. When immersed in a hydrogen peroxide bath, the colloids convert chemical energy into active motion. The general purpose of physicists is to understand the mechanisms of self-aggregation and the formation of clusters. Remarkably, such mechanisms are typical of many living systems (e.g, cells, sheep flocks, birds, fishes swarms, etc.). To model the behavior of colloids, a natural approach is to derive the models from the identification of the individual trajectories in recorded video sequences of colloidal suspensions.

In this contribution, we address the task of segmenting and tracking individually a large number of identical colloids in long

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boyang.gao@ec-lyon.fr (B. Gao), masnou@math.univ-lyon1.fr (S. Masnou), liming.chen@ec-lyon.fr (L. Chen), isaac.theurkauff@laposte.net (I. Theurkauff), cecile.cottin-bizonne@univ-lyon1.fr (C. Cottin-Bizonne), zhaocsu@163.com (Y. Zhao), shih@njit.edu (F. Shih). video sequences corrupted with severe illumination changes. In contrast with previous approaches in the literature [3,4], frequent interactions among the colloids are possible, large clusters can form and move, and the motion of colloids can be very complicated [2]. In particular, we can neither assume any motion regularity nor use a prior model to predict colloids location. This is a major difference with many classical tracking methods.

Our work is based on video captures of a two-dimensional suspension of self-propelled colloids [2]. By two-dimensional, it is meant that the colloids being heavy, they settle at the bottom of the observation cell and only 2D motions are observed. In particular, the colloids being observed from below, there is essentially no occlusion phenomenon. We propose a framework to jointly segment, localize and track each colloid. The difficulty of the detection task follows from the severe intensity inhomogeneities in each frame, and the highly cluttered colloids in low-contrast images. The method that we propose in this paper can actually handle even more complicated situations, e.g. it is also applicable to dense assemblies of passive colloids, such as colloidal glasses and gels.

To sum up, our contribution is as follows:

 To perform high-quality segmentation of individual colloids in each frame, we propose to combine a level set formulation of an active contour model and the circular Hough transform. This



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combination allows us to handle the severe intensity inhomogeneities and the high density of colloids.

- We build a graph over all frames with colloids as vertices. Edge costs depend only on the distances between colloids, and do *not* rely on any model of regularity or linearity for the motion. It is only assumed that a given colloid does not move too fast between two frames.
- We propose a modified min-cost/max flow approach to recover simultaneously and globally from the graph all individual trajectories of colloids. More precisely, we combine the successive shortest path (SSP) method and a tag-then-delete approach which allows us to find all possible meaningful paths in the graph. No additional parameter is needed to guide the calculation.
- Unlike other methods validated only on simulated image data, we evaluate quantitatively our approach on a real benchmark of video sequences of active colloidal suspensions. These videos have been annotated by several graduate students. As far as we know, there is very limited previous work using real dataset with human observations labeling the ground truth, for the obvious reason that it is a tedious task to track all particles in long video sequences. Instead, most methods first evaluate on a synthetic benchmark [5–7] with other standard algorithms, then provide performances on real data, e.g. cells in fluorescence image sequences.

The remainder of this paper is organized as follows. In Section 2, we present a survey on previous contributions on object tracking. In Section 3, we introduce our detection algorithm, the graph construction, the modified min-cost/max flow algorithm, and how the optimal solution is computed. In Section 4, our real-data benchmark is introduced and extensive experiments are presented to validate our method. Finally, we conclude in Section 5.

#### 2. Related work

There is a huge literature on detection and tracking of individual or multiple objects [8,7,9]. The different approaches divide roughly in two categories: detect-then-track, or joint detection/tracking. In this paper, we use the detect-then-track paradigm.

#### 2.1. Particles detection

Most particle detection algorithms involve three stages [10,7,6]: (i) noise reduction, (ii) signal enhancement, and (iii) signal thresholding. Techniques range from simple thresholding [11] to wavelet filtering [12], Gaussian smoothing, local maxima detection [13], morphological processing [14], linear and nonlinear model fitting [13], or centroid estimation [15].

#### 2.2. Multiple object tracking

Multiple object tracking has been intensively studied by researchers, and can be roughly divided into two classes [16]: (i) probabilistic methods. (e.g. Kalman filters [17], particle filters [18], multiple hypothesis tracking [19], inference on Bayesian network [20], joint probabilistic density association filters [21]), Monte Carlo Markov Chains methods [22]; (ii) deterministic methods (e.g., nearest neighborhood, minimum-cost [23–26], shortest path [27,28], minimal paths [29], Hungarian algorithm [30], integer programming [31]).

Most proposed algorithms are locally greedy: they involve a low-level tracker in a small time window (two frames or three) to obtain tracklets, and then link the partially tracked fragments using methods like network flow [26], linear programming [32], matching algorithm [30], Bayesian network [20], or solving a set cover problem [24]. These local greedy trackers are applied widely for the sake of low computational cost, nonetheless they tend to have identity swap errors. In addition, they are not easily correctable a posteriori when future information is included. Another drawback is that most of these methods can easily miss the global optimal solution. In contrast, both the Multiple Hypothesis Tracking method and the Monte Carlo Markov Chains method look for the largest nonconflicting trajectories of all objects satisfying the expected motion behavior. However, none of it can guarantee a globally optimal solution in sub-exponential time.

#### 3. Proposed framework for colloids detection and tracking

#### 3.1. Accurate active colloids detection

The difficulty of detecting particles may yield detection errors: some particles are missed and some artifacts are wrongly considered as being colloids. The experimental setting used in this paper complicates the detection even more: all images have low contrast-to-noise ratio, and they are subject to uneven illumination, i.e. the flat-field from the lamp causes the interior to look brighter than near image boundaries (see Fig. 1(a)). In addition, objects can be highly cluttered, which can cause severe ambiguities in the tracking stage.

We propose an accurate method to detect individual objects by combining the level set method proposed in [33] and the modified Circular Hough Transform (CHT) [34]. It is known that all objects in the image are round-shape spots, although some colloids may have deformations due to twinkle or uneven illumination. The Circular Hough Transform has been proved efficient in detecting circle targets thanks to its nice properties such as the robustness to noise, and invariance to slight occlusion and illumination.

However, when dealing with real-world images, the circular Hough transform can miss potentially targets altered by intensity inhomogeneities. In this paper, we adopt a robust level set variational model [33] to overcome the difficulties arisen from such inhomogeneities. More precisely, we use the region-scalable fitting (RSF) energy which quantifies how well, given a contour *C* in the image domain  $\Omega$ , the image intensities in the outer and inner domains with respect to *C* are well approximated locally by two functions  $f_1$  and  $f_2$ :

$$e^{RSF}(C, f_1, f_2) = \int_{\Omega} \left( \lambda_1 \int_{\text{inside}(C)} \mathbf{K}_{\sigma}(\mathbf{x} - \mathbf{y}) |I(\mathbf{y}) - f_1(\mathbf{x})|^2 d\mathbf{y} + \lambda_2 \int_{\text{outside}(C)} \mathbf{K}_{\sigma}(\mathbf{x} - \mathbf{y}) |I(\mathbf{y}) - f_2(\mathbf{x})|^2 d\mathbf{y} \right) d\mathbf{x} + \nu |C|.$$
(1)

In this model,  $\Omega$  is the image domain,  $\lambda_1$ ,  $\lambda_2$ ,  $\nu$  are positive constants,  $K_{\sigma}$  is a Gaussian kernel whose standard deviation  $\sigma$  tunes the locality of the approximation, and the length |C| of *C* is a regularization parameter that avoids spurious contours when the energy is minimized. The fitting energy  $\varepsilon^{RSF}$  is able to segment objects even in severe illumination conditions. Indeed, the approximating functions  $f_1$  and  $f_2$  are not necessarily constant within the outer and the inner domains outside(C) and inside(C), in contrast for instance to classical active contour approaches as the Chan-Vese model [35]). This allows a good robustness to light changes. As in [33], we adopt a level-set formulation so that the associated minimizing flow can handle topological changes.

The proposed detection method combines RSF and CHT. It can segment individual tiny objects in dense populations in the presence of noise and intensity inhomogeneities. Fig. 1 shows some results of colloids detection. Obviously, Fig. 1 (a) is a difficult image for the task of segmenting individual tiny colloids from poor Download English Version:

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