Visual Motion Analysis of Nanoplatforms Flow under an External Magnetic Field

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ABSTRACT

We describe a visual tracking algorithm for nanoplatform motion analysis, where computer vision and image processing techniques are used as the essential enabling tools for the modeling and design of nanostructure systems. The proposed algorithm robustly tracks multiple nanoplatforms despite their frequent disappearance, Brownian motion, and cluttered low contrast imagery. We have studied quantitative relationships between nanoplatform sizes, fluid flow rate and viscosity, external magnetic field strength and their effects on the trajectories. With a visual analysis graphical user interface developed for this project, we have explored the nanostructures, consisting of fluorescent $PbSe$ quantum dots coupled with magnetic $\gamma-Fe_2O_3$ nanoparticles in fluids mimicking the viscosity of the bloodstream. Based on the present work, it may be possible to develop nanoplatforms to be utilized for the simultaneous identification, mapping, targeting and destruction of cancer cells.

Keywords: Visual tracking, nanoplatforms, velocimetry, trajectory exploration

1 INTRODUCTION

In this paper, we employ certain tools from computer vision in order to help researchers in the rapidly developing field of nanofluids, which has many possible diverse applications. It is anticipated that the utilization of nanofluids will have a direct and profound impact on drug delivery, imaging and sensing and more specifically, cancer therapeutics. This is primarily due to the ability to design novel materials at the nanoscale that when coupled with recent innovations in analytical and imaging technologies, make it possible to measure and manipulate novel and complex structures in this size regime.

The problem formulation is as follows. The recorded video sequence of nanofluid is processed in order to extract nanoplatform trajectories (*tracks*) and different visual properties, e.g., size, orientation, and average brightness. The algorithm should be able to manage new and lost tracks, as well as temporarily disappeared tracks. The extracted trajectories are used for the statistical analysis of the nanoplatforms' velocity and direction. This data can be used further for physical modeling of nanoplatform motion and the given system's response to an external magnetic field.

In the analysis, we encounter the difficulties of low contrast cluttered frames with frequent disappearance and reappearance of nanoplatforms due to the three-dimensional nature of their trajectories. Such behavior was not fully addressed in the literature on cell or particle tracking velocimetry before. A good review of modern tracking methods for images obtained by a microscope can be found in Wu *et al.* [7]. Due to the size effect, the results of these previous studies also may not be applicable to flows of nanofluids, for which little has been seen in the literature (e.g., [5]). More recent studies provide a robust localization for hundreds of particles in each frame (e.g., [2]), but the management of the new tracks is still not sufficient. The preliminary work on the characterization, modeling, and tracking of the considered nanoplatforms is described in [3], [4].

Unfortunately, despite the unprecedented research activity involving the use of nanoparticles for targeted drug delivery, imaging and sensing, the imaging and tracking techniques that have been used in this context are rather limited in scope, and hence, very little information about the dynamic behavior of these systems has been obtained. Therefore, the general aim of this work is to develop novel visualization and tracking capabilities that could be used in conjunction with nanoparticle design and synthesis in order to develop nanofluids that would be optimally-suited for their intended applications.

This work developed a special procedure that overcomes the aforementioned obstacles, by the consideration of the following points: (a) Criteria for appropriate visibility conditions; (b) Estimation of the direct velocity; (c) Automatic initiation and termination of nanoplatform tracks; (d) Consideration of centroid tracking also of non-spherical nanoplatforms; (e) Trajectory update is based on a current frame only; (f) Novel approach of tracking by filtering (e.g., see [1]), based on brightness and contrast correction.

The rest of this paper is organized as follows. In Section 2, the algorithm for trajectory construction is described. In Section 3, the representative results and discussion are presented.

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2 ALGORITHM DESCRIPTION

The algorithm for the construction of trajectories consists of three basic components: prediction of the location for each track, image based measurement, and estimation with measurement-track association. The idea is to create new trajectories in the first frame from all sufficiently bright nanoplatforms. For the next frames, the trajectory continuation is predicted by constant velocity model [1]. The measured closest to the prediction neighbors (bright blobs) are considered as possible candidates for the trajectory continuation. The most probable candidate is added to each trajectory. The bright blobs that are not associated with the existent trajectories start the new trajectories. If a given nanoplatform disappears for a few frames, the track continuation is generated by the prediction procedure.

2.1 Prediction

Let us define the state $X(k)$ of the tracked system at frame k (for each nanoplatform) to include the location of the center of mass (from now on called the *centroid*) (x_c, y_c), velocity (v_x, v_y), and visibility P, which will be explained later. The state $X(k)$ is set to be a function of only the previous state $X(k-1)$, according to the Markovian assumption. In the initialization step ($k = 0$), all the detected particles from the first frame were used to initialize the trajectories. The centroids $(x_c(0), y_c(0))$ were initialized at the values of the detected nanoplatform centroids. The initial velocities were set to 0, and the visibilities to 1. In the prediction step ($k > 0$), suppose that the kinematic model of motion is the constant velocity model [1]:

$$\begin{cases} x_c(k+1) = x_c(k) + \Delta t \cdot v_x(k) \\ y_c(k+1) = y_c(k) + \Delta t \cdot v_y(k) \\ v_x(k+1) = v_x(k) \\ v_y(k+1) = v_y(k) \\ P(k+1) = P(k) \end{cases} \tag{1}$$

where Δt denotes the reciprocal of the video frame rate. Using (1) one defines a search region for the nanoplatforms in the following frame.

2.2 Measurement

The images recorded by video camera can be roughly described as a mixture of light scattered by nanoplatforms, light scattered by a partly transparent polymer fluid, and stationary background, which is caused by small defects. The goal of measurement is to separate the image of the nanoplatforms from the background and the fluid, and to compute the centroids and other properties of the nanoplatforms.

The first step is to use background subtraction to remove the stationary background. The statistical background model proposed by Stauffer and Grimson [6] works well with type of video of interest in this work, but this algorithm updates the background dynamically, and needs some time to learn the background. This property limits the applicability of [6] to our videos, where extraction of maximum number of trajectories is needed. We propose to use a simpler algorithm for background removal. The simplest model for the semitransparent background is:

$$I = \alpha B + (1 - \alpha)F, \tag{2}$$

where I is the obtained image, B is the estimated background, and F is the foreground that we want to extract. Here α is the transparency coefficient ($0 < \alpha < 1$). To validate that both sides in (2) are positive, we choose:

$$\alpha = \min_{\forall pixels} \left(\frac{I}{B} \right). \tag{3}$$

In order to estimate the background B, we compute a temporal trimmed average of N frames before and after the current frame, where 50% of outliers are trimmed and not included in the average computation. The parameter N is chosen to make sure that at least 50% of time every pixel belongs to the background. In addition, the trimmed temporal standard deviation σ is computed. The value of σ specify a possible background variation.

Using (2) and (3) we estimate the foreground (nanoplatforms and fluid) by the following formula:

$$\hat{F} = \begin{cases} \frac{I - \min\left(\frac{I}{B}\right)B}{1 - \min\left(\frac{I}{B}\right)}, & \text{if } I - B > 3\sigma \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

To remove the noise caused by the fluid, we apply a band pass filter (BPF) to the images $\hat{F}$. In general, this operation provides the images described in Figure 1-B. The filtered image is converted to a binary by thresholding. The remaining noise and small holes are removed by the morphological *closing* operation with disk structuring element [7]. Finally, connected image labeling is applied to binary images; centroids and other important properties of the connected elements are computed.

2.3 Estimation

We have implemented two methods of estimation and association of the measured centroids to the existent trajectories. The first method is based on the Joint Probabilistic Data Association Filter (JPDAF) [1]; the details will be published elsewhere. This method presupposes a constant number of nanoplatforms in every frame. The second method is based on the Nearest Neighbor Standard Filter (NNSF) [1]. This method is simpler and it removes the limitation of constant number of targets.

The NNSF continues each trajectory to the nearest measured neighbor. We use the modification of this filter as follows. In the measurement step, we estimate the location of the nanoplatforms, which were extracted from the filtered frame. For each trajectory, the filtered frame is searched for prominent peaks (close to the locations selected in the prediction step). The obtained peaks are classified into one of three predefined groups: (a) *Particles* - bright and prominent peaks; (b) *Suspects* - peaks with an average brightness, but still discernible from the background; and (c) *Phantoms* - barely visible peaks. For automatic classification, we selected manually two thresholds for brightness, T_1 and $T_2 (0 < T_2 < T_1 < 1)$. These thresholds separated among the particles, suspects and phantoms. The parameter of visibility $P(k)$ controls the the termination of the trajectories. If this parameter is high and the target disappears, this parameter decreases and the trajectory is continued by prediction, if the parameter is low, then the trajectory is ended. If after a few frames the target reappears, then P increases.

We denote the average brightness of the measured blob as $f(k)$. The estimation step ($k > 0$) consists of the updating of the location of nanoplatforms and the addition of points to appropriate trajectories as follows:

$$(\hat{x}(k+1), \hat{y}(k+1)) = \begin{cases} \text{not updated, if } P(k) > T_1 \text{ and } f(k) \leq T_2, \\ \text{does not exist, if } P(k) \leq T_1 \text{ and } f(k) \leq T_2, \\ (x_c, y_c), \quad \text{otherwise} \end{cases} \tag{5}$$

$$(\hat{v}_x(k+1), \hat{v}_y(k+1)) = \begin{cases} \text{not updated, if } P(k) > T_1 \text{ and } f(k) \leq T_2, \\ \text{does not exist, if } P(k) \leq T_1 \text{ and } f(k) \leq T_2, \\ \left(\frac{x_c - x(k)}{\Delta t}, \frac{y_c - y(k)}{\Delta t}\right), \quad \text{otherwise} \end{cases} \tag{6}$$

$$\hat{P}(k+1) = \begin{cases} P(k), \text{ if } P(k) > T_1 \text{ and } f(k) > T_1 \\ \text{does not exist, if } P(k) \leq T_2 \text{ and } f(k) \leq T_1 \\ 2P(k), \text{ if } P(k) \leq T_1 \text{ and } f(k) > T_1 \\ 0.5P(k), \quad \text{otherwise} \end{cases} \tag{7}$$

where (x_c, y_c) is the centroid location of the closest bright peak, obtained in the measurement step. The option "does not exist" in the expressions given above means that the trajectory is ended; the option "not updated" means that in the following frame the predicted values will be used.

The obtained trajectories were smoothed by a low pass filter to remove the Brownian motion effects. The trajectories shorter than five points were deleted. The statistical data on the velocities and direction of nanoplatforms allowed to update the physical model, as described in [3], [4].

A graphical user interface (GUI) was developed, implementing an algorithm discussed above, enabling automatic determination of the location of a nanoplatform from raw video data and construction of its trajectory. The GUI was developed with a MATLAB program (see Figure 1). This GUI allows the user to tune different detection parameters, to choose visibility levels, activate filtering process, and to save the extracted data for statistical analysis.

3 RESULTS AND DISCUSSION

The nanoplatforms were visualized through an optical microscope NANOSIGHT LM10 as small points of scattered light, and their position was recorded by a CCD camera with resolution 480×640 pixels. In Figure 2, we show the video frames at three different times, a representative trajectory plots of several nanoplatforms, and representative weighted frequency of appearance over 300 consecutive frames versus the deviation angle, θ, and velocity v of the trajectory with respect to the chamber axis (as derived by the algorithm).

We have demonstrated that magnetic fields of smaller than 1 Tesla applied to the flow of the nanoplatforms, can significantly affect their motion [3]. The analysis of the videos obtained from the experiments has shown that the nanoplatforms have a stable number of nanoparticles under different flow rates and different magnetic field strengths. This fact indicates that the conjugation can sustain the external forces. We have analyzed the direction of nanoplatform motion both with and without an external magnetic field, and confirmed that the trajectories can be controlled by this field. The magnetic force is higher than the fluidic force in the perpendicular to the flow direction, except the cases of relatively high viscosities and large flow rates.

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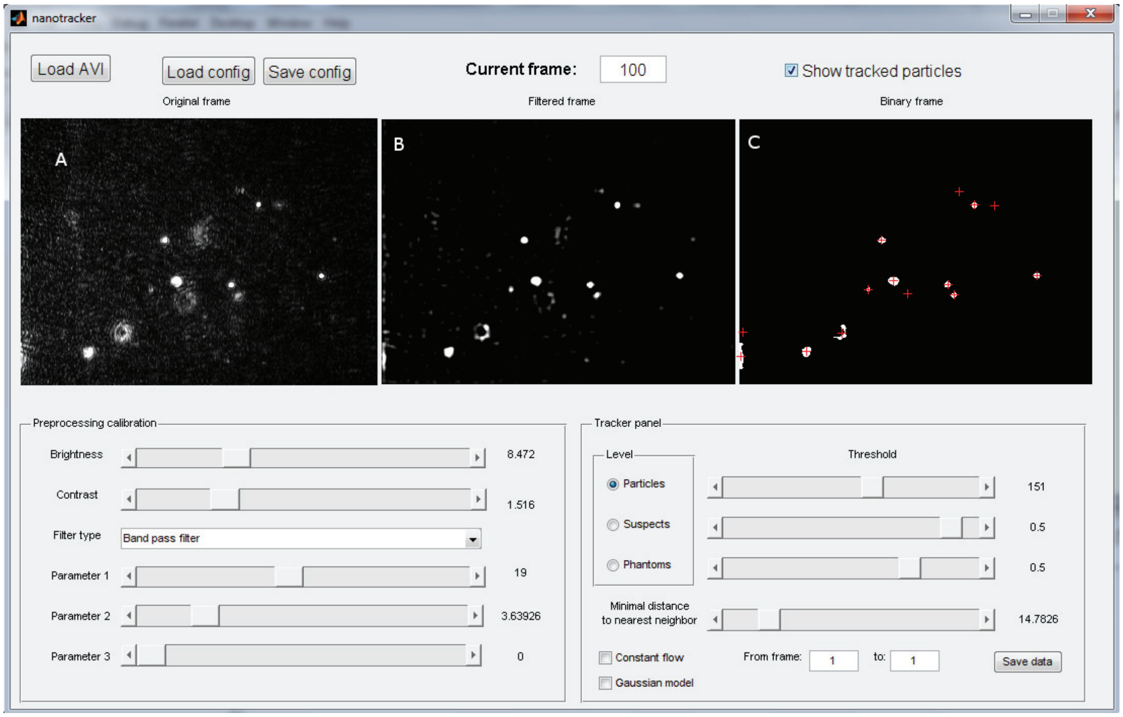

Figure 1: The "Nanotracker" Graphical User Interface. (A) an original noisy video image with a poor contrast, (B) a filtered preprocessed image, and (C) a binary decision image. A location of a detected nanoplatform is memorized as '1' (white), and the background pixels are memorized as '0' (black); a cross on the decision image marks a nanoplatform centroid.

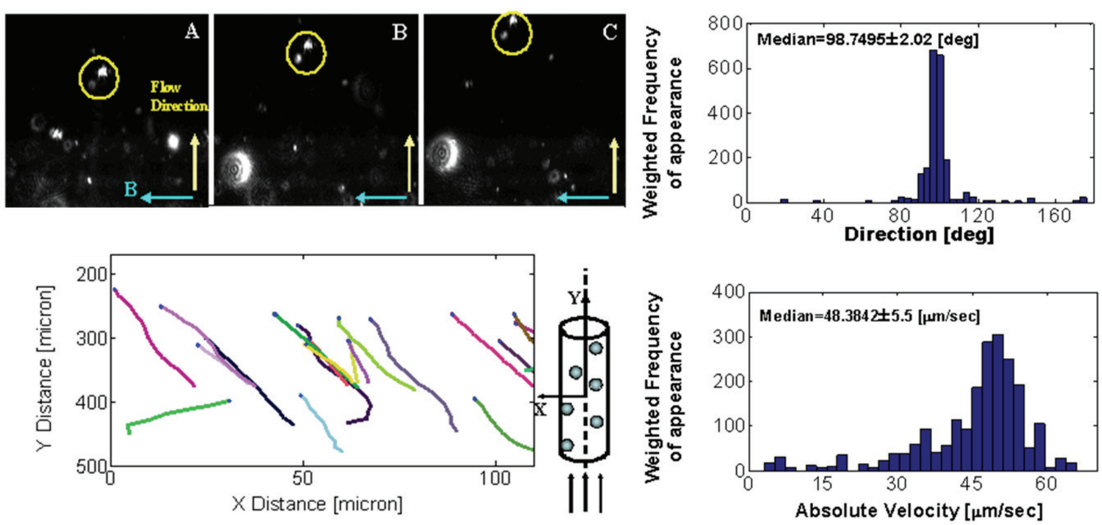

Figure 2: The representative results. Left: Video frames at three different times and trajectory map of the detected nanoplatforms. Right: Velocity and direction distribution for the entire video. A fluid with a viscosity of 1.73cP and flow rate of 0.9 mL/h under an external magnetic field, revealing an average velocity of 48μm/sec and 99° deflection from the abscissa axis.