

Drop Breakup Characterization and Prediction when Flowing Through a Narrow Constriction

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Abstract— We created a system to detect drops in videos of a concentrated emulsion flowing through a tapered channel with a constriction. The system automatically detects whether each drop breaks or remains intact. A simple prediction model is also created to predict whether a drop breaks given information about the drop prior to its entrance into the constricted channel. This model was manually trained on a 2000-frame training video ($N_{\text{train}}=15$). An extremely simple model based on a metric involving a nearby drop was found to be extremely effective, resulting in a 0% error on the training set. Our classifier achieved an accuracy of 88.4% and an F1-score of 86.5% on a test video ($N_{\text{test}}=206$).

Keywords—Microfluidics, Drop breakup physics, Object tracking, Statistical learning

I. INTRODUCTION/MOTIVATION

Bioreactors are small containers to test properties of a drug or biological substance. In recent years, there has been immense interest in using microscale drops as bioreactors where single or multiple biomaterials are inserted into the drops to undergo chemical reactions [1,2]. One advantage of drop reactors when compared with solid wall reactors like the 96 well plate is that a large number of drops are able to be generated and analyzed in a short amount of time. Assays that can achieve such a feat are called “high-throughput” assays. However, one downside of using drops as biological reactors is that drops can break up into smaller drops at high flow velocities. This breakage is observed experimentally.

In the experimental setup, microscale drops are generated in a tightly packed configuration called a “concentrated emulsion”. The emulsion is then pumped into a tapered microfluidic channel connected to a constricted channel. The constricted channel allows only a single row of drops to flow through at a time. When the concentrated emulsion is in the constricted channel, it is effectively a 2-dimensional layer of drops, also known as a monolayer.

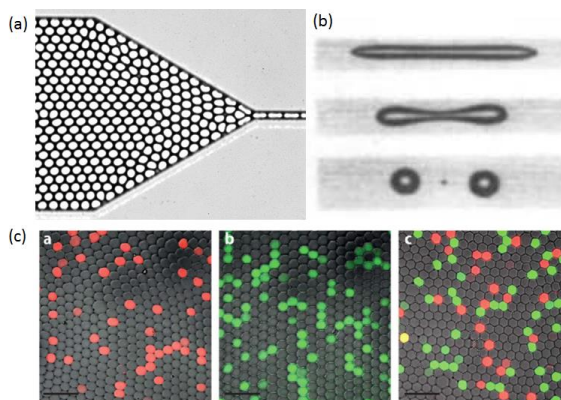


Fig. 1: (a) Concentrated emulsion flowing through a tapered channel into a constricted channel. (b) Single drop breakup in an unconfined flow [3]. (c) Example of a drop reactor [1].

The physics of single drop breakup in flow conditions has been well studied [3]. However, when introducing an isolated single drop through this channel geometry at the range of flow velocities that we are interested in, it was found that the isolated drops do not break. On the other hand, drop breakup is observed when a concentrated emulsion is flowing through the channel geometry at that same range of flow velocities. This leads us to believe that the breakup of a drop in a concentrated emulsion when flowing through a narrow constricted channel is caused by drop - drop interaction and drop - wall interaction.

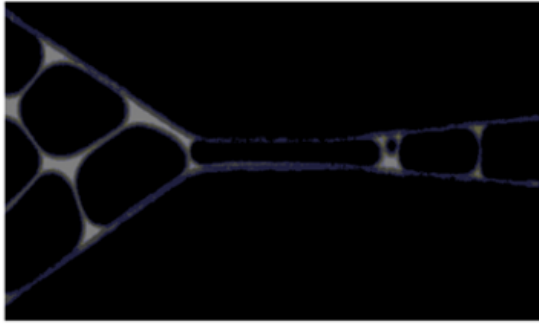


Fig. 2: Example frame of video.

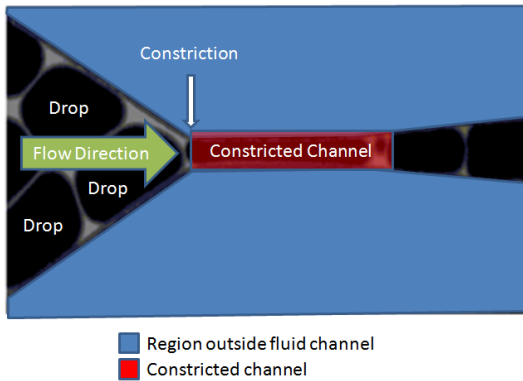


Fig. 3: Visualization of important geometric regions in video frames.

II. RELATED WORK

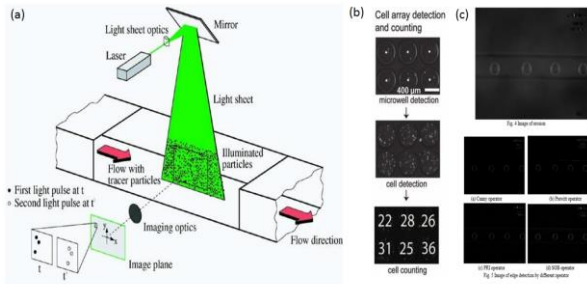


Fig. 4: (a) A typical PIV setup [4]. (b) Cell counting in a solid well [5]. (c) Drop characterization in a microfluidic channel [6].

A. Particle Image Velocimetry (PIV) and Traction Force Microscopy (TFM)

Our system is heavily inspired by the flow and force visualizing image processing technique, Particle Image Velocimetry (PIV) [7] and Traction Force Microscopy (TFM) [8]. Both techniques are essentially the same. To prepare for

the technique, fluids or solids are embedded with particles, and displacement of the particles are recorded as the fluid flows or as stresses are applied to the solids. The images taken are segmented into individual windows of equal sizes. Each window is used as a template, which is then matched against the next frame to determine an estimated displacement for that window. The window displacement, in turn, is used as an estimate of the average displacement of the particles in that window. For the case of solids, this yields the material strain, and for the case of fluids, this yields the flow velocity of the particles. We use a similar consecutive frame comparison in our system, but without template matching.

B. Cell counting in solid well and drop detection and characterization

The system presented in this report is also inspired by image processing techniques that are used to detect objects. For example, Kachouie et al. presented an algorithm for counting cells in solid wells [5]. Furthermore, WeiWei et al. presented an algorithm based on edge detectors to compute drop volume of drops flowing through a fluidic channel [6].

III. GOALS

The goals of the current project were to 1) process videos of drops into a form suitable for analysis 2) record high-level data about drops during critical periods of time, and 3) create a simple predictor model to classify whether drops break as they enter the central constrictive channel.

IV. DATASET

The input data for this project consists of a series of video files, each showing a snapshot of drops moving in the channel under study. Videos were captured with a high speed camera, single channel per pixel, at 512x256 resolution, at 21052 fps. A dataset of two videos with 2000 (train set), 20000 frames (test set) respectively was used. The videos were cropped (in time) from a single source video, thus the experimental setup does not vary across the videos.

V. METHODS

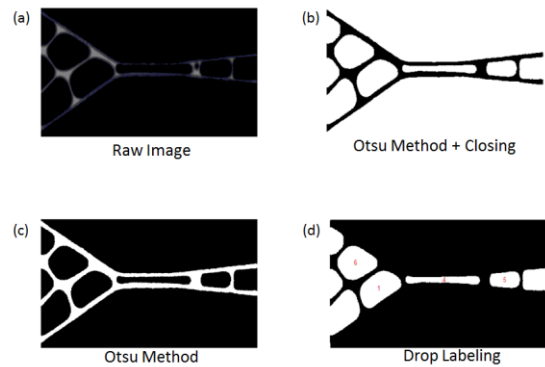


Fig. 5: Intermediate results of image processing used in algorithm.

A. Image Binarization

To achieve goal (1), several preprocessing steps are used. The first step is to read a drop video file into MATLAB. Then, for each (grayscale) frame, preprocessing steps are carried out. First, each frame is binarized using a manually selected threshold. This threshold was determined by starting with the Otsu threshold [9], then adjusting such that the drop boundaries were acceptably maintained. Second, unimportant areas of the image (those outside the fluid channel) are thrown away using a manually calculated polygonal mask.

B. Morphological closing

Third, morphological closing is performed to heal any defects in the binarized image [10]. Several different structural elements and sizes were tested to determine which is suitable for the images presented in this report. The morphological closing had an unnoticeable effect when the size of the structural element is too small. However, important geometrical information is lost when the size of the structural element is too large. For example, the eccentricity of a drop might be distorted, or the drop could disappear entirely if its size is smaller than the structural element. Thus, there is an optimal structural element size for the images that were used in this project. A few structural element shapes were tested (square, disk and diamond). Morphological closing results were similar but it was determined visually that a square-shaped structural element provided the best result. The structuring element that yielded the best qualitative performance for the morphological closing was a square with side length 8.

C. Drop detection and characterization

Fourth, blob detection and properties are obtained using MATLAB's `regionprops` function. Each detected blob corresponds to a distinct drop of fluid. Fifth, the aggregate blob data is saved into an array. The result of the preprocessing phase is an abstract video, where each frame contains not an image, but an array of data resulting from processing the corresponding frame in the original video.

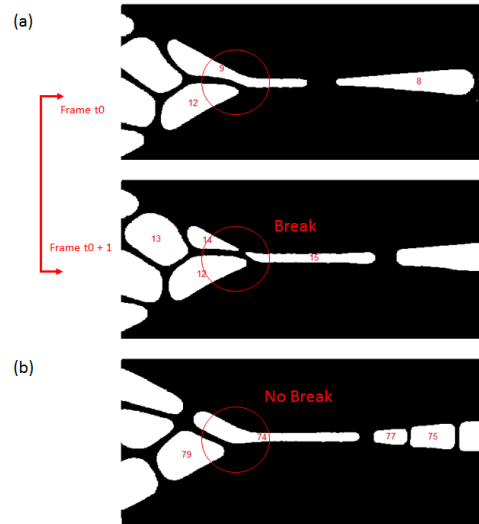


Fig. 6: Frames of drop that break (a) from frame t_0 to t_0+1 and drop that stays intact (b).

To achieve goal (2), the following steps are performed. First, a phase of drop identification and tracking is performed. Drops are assigned an ID from an incrementing counter, which increments whenever a new drop enters the frame, or an old drop splits up into two new drops. To track drops across frames, a simple method is used. Namely, for a given frame, the centroid of each drop is compared with the centroid of all drops from the immediately preceding frame. If centroids in this comparison are within a small, fixed-size disk from each other, then the two drops are assigned the same ID. The positions of drops from frame to frame is, in general, within a few pixels due to the high frame rate of the camera. This simple tracking analysis is carried out for the entire abstract video, obtaining a new abstract video of drop identities (along with all of the information obtained from goal (1)).

D. Drop breakup detection

The next subgoal is to identify critical events (on a per-drop basis) that occur as the drops moved from left to right across the image. A critical event occurs whenever either a drop breaks, or when a drop enters the constricted channel. For each critical event emitted, our system saves the time series of drop geometric parameters extending backwards in time until the drop appeared. Additionally, our system saves the displacement vector to the nearest drop that has a lower x-coordinate. We refer to this nearest drop as the “companion” drop. Due to inter-drop interaction, displacement to companion was suspected to be critical for predicting whether breakage occurs.

E. Prediction model

To achieve goal (3), we aimed to create a classifier that took as input a video and drop index, and would predict whether that drop would break. Of course, only information corresponding to times before the possible breakage could be

used to perform this prediction. To (manually) train the classifier, the following steps were performed. First, a training set was constructed by running our system on a short 2000-frame video. The saved data for each constriction entrance event were manually examined in an attempt to understand important predictors of breakage. It should be noted that drops, if they are to break, always break slightly after they enter the constriction. Although many predictive factors could be important in predicting drop breakage, it was immediately apparent that the x-coordinate of the displacement vector to companion was a strong factor. For (absolute value of) x-coordinates higher than 31, 0% of drops broke, and for x-coordinates lower or equal to that threshold, 100% of drops broke ($p < 0.001$), for a training error of 0%. Therefore, for this project, it was determined to create a simple classifier that predicted only based on x-coordinate of displacement to companion. With that in mind, the classifier was now “trained”.

To evaluate the performance of the classifier, a long, 20000-frame test set video was analyzed using our system. Ground truth (i.e., whether or not each drop broke) was automatically determined by an analysis of drop IDs as they left the constricted channel. This ground-truth determining algorithm constructs a list of all the drop IDs that ever appear upstream of the constriction, and an analogous list for drop IDs that ever appeared downstream. The lists are then compared against each other. If a drop appeared upstream, but it never appeared downstream, the upstream drop is recorded as broken. Else, the upstream drop is recorded as intact. With ground truth in hand, testing of the classifier could begin. For each channel entrance event, the classifier was fed the x-coordinate of the displacement to companion, and it outputted a breakage prediction (true or false). The predictions were compared against ground truth to generate a confusion matrix.

VI. RESULTS

A. Drop Geometric Parameters Before Critical Events

Table 1. Sample table of geometric properties of the drops that were recorded in a frame

Drop ID	x-coordinate (pixel)	y-coordinate (pixel)	Drop area (pixel ²)	Drop perimeter (pixel)	Major axis (pixel)	Minor axis (pixel)	Orientation (degrees)
25	120	132	4688	352	165	41	4.32
28	108	90	2279	212	94	33	-21.99
26	96	172	725	118	54	18	22.11
29	280	122	2018	282	154	18	0.20
27	425	122	3853	306	149	35	0.61

In the table above, drop parameters that were recorded for that frame are shown. Drop ID is presented to label each drop in the frame. The x- and y-coordinates of the drops are recorded, as it is important to know where the drops are located and to compute physical parameters like horizontal drop offset. The drop area, drop perimeter, drop major axis,

drop minor axis, and drop orientation are also recorded to study drop breaking.

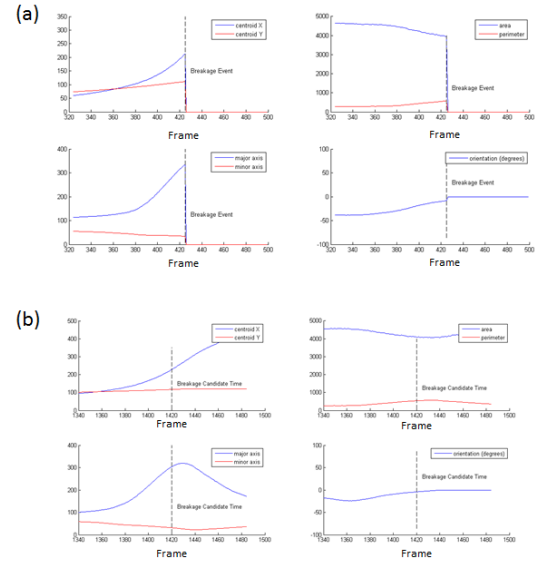


Fig. 7: (a) geometric properties of an example drop that breaks and (b) geometric properties of an example drop that remains intact.

We now examine the time series of these properties as the drops approached the channel constriction, where they were most likely to break. A representative set of time series for both breakage and non-breakage events is shown in (Fig. 7). A qualitative analysis of these plots reveals that the geometric parameters appear very similar for both breakage and non-breakage events. Thus, we conclude that none of the geometric parameters studied in this experiment (eccentricity, area, perimeter, major axis, minor axis) are crucial to predict breakage. However, we believe more sophisticated metrics of drop geometry (such as a numerical measure of concavity) would yield a more significant predictor.

Table 2. Classifier Results on Test Set

	Predicted: No	Predicted: Yes	
Actual: No	105	12	117
Actual: Yes	12	77	89
	117	89	Total: 206

Sensitivity	0.86517
Specificity	0.89744
F1 score	0.86517
Accuracy	0.8835

As can be seen from the confusion matrix, the results are (in our opinion) quite good, with an accuracy of 88.4% and an F1-score of 86.5%, far better than the 50% that would be expected from a classifier with no predictive power. To our knowledge, no previously existing procedure attempts to predict microscale drop breakup in a concentrated emulsion from images, and thus we have established a baseline performance. Even with our simple predictor which only analyzed a single real variable (x-distance to companion), a fairly high accuracy was obtained.

VII. DISCUSSION

Although our algorithm works well for the set of images that are used in this report, there are some limitations to the algorithm presented here. First, the intensity contrast between a drop and its surrounding fluid has to be significantly high for correct operation, because this contrast allows our algorithm to detect the boundary of the drops. If the contrast between a drop and its surrounding fluid is low, the boundary of the drop cannot be robustly distinguished.

Furthermore, our algorithm will not be able to track drops that travel more than a few pixels during one exposure time of the camera, resulting in a blurred drop image. A blurry drop will not have a distinct drop boundary which will make it hard for the algorithm to detect the drops, much like when the intensity of the drops and surrounding fluid is similar.

When detecting pairs of drops, our algorithm did not consider the full $O(n^2)$ combinations of drop IDs, rather, only consecutive drop IDs were considered. This heuristic could be improved to the full $O(n^2)$ pairs to increase the effective size of the training and test sets.

The discovery of the x-distance to companion as the dominant parameter in predicting drop breakup is interesting. Our hypothesis for why the x-distance is an important factor in drop breakup is that x-distance is a strong predictor of what is known as “characteristic time” of a drop, which is time needed for a pair of drops to rotate around each other such that the drops are horizontally aligned. From prior experiments, it is

known that large characteristic times lead to breakage of one of the drops in a pair. [11]

VIII. CONCLUSION AND FUTURE WORK

In this report, we created an algorithm to track and detect drops flowing through a narrow constricted channel and determine the fate of the drop (intact or break). A simple prediction model was also implemented to predict drop breakup when given x-coordinate of displacement to companion. For future works, a more sophisticated prediction model should be implemented once more key predictors of breakup are found from other experiments.

IX. APPENDIX: WHO DID WHAT:

Jian-Wei Khor

- Drop detection and tracking code implementation
- Qualitative and quantitative analysis of important predictors of drop breakup
- 25% of final report exposition

Troy O’Neal

- Statistical framework of classifier
- High-level drop detection and tracking requirements generation
- 75% of final report exposition
- Any tasks not mentioned in the above list were performed jointly.

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