

Supplementary Materials: Real-time Parameter Evaluation of High-speed Microfluidic Droplets Using Continuous Spike Streams

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1 SYNTHETIC DATASETS PREPARATION

To validate the accuracy of the spike-based parameter estimation method, we simulated spike streams with different droplet parameters as follows: To begin, we generated a video stream imitating the flow of droplets, which contains N frames of grey image with a resolution of $W \times H$ pixels. The droplets are represented by circles moving by pixels through the plotting canvas from right to left. For the synthetic data, the droplet velocity(mm/s) can be written as:

$$\hat{v} = \frac{Nsp}{1000} \quad (1)$$

where p is the pixels moved per frame. N and s are the frame rate and pixel size (μm) of the spike camera.

With a constraint where each frame can only shift by one pixel at minimum, the droplets in the simulated data have a minimum velocity of $\frac{Ns}{1000}$ (mm/s). To achieve the generation of droplets with arbitrary velocity, we introduce an interpolation factor k , using bilinear interpolation to expand the t-dimension of the frame sequence, effectively reducing the actual scale of movement per frame and making the simulated droplet velocity more aligned with real experimental conditions. Note that the total generated frames remain N after interpolation. In this case, the pixels moved per frame become $\hat{p} = \frac{p}{k}$. And the final droplet velocity(mm/s) can be expressed as:

$$v = \frac{Ns\hat{p}}{1000} \quad (2)$$

Furthermore, the size $S(\mu m)$ and frequency $f(Hz)$ of the generated droplets can be calculated as:

$$S = sd \quad (3)$$

$$f = \frac{N}{k(d+i)} \quad (4)$$

where d is the pixel diameter of the simulated circles, and i is the pixel interval between the boundaries of adjacent circles.

We can control the droplet velocity by changing the number of pixels moved per frame \hat{p} , and simulate different droplet sizes and generation frequencies by adjusting the diameter d and interval i of the circles. It is worth mentioning that there is a constraint relationship between droplet velocity and frequency. A faster droplet velocity implies a higher fundamental frequency. Adjusting k will also influence the value of frequency. Finally, we use the generated image sequence as the input of Spikingsim[1] to simulate corresponding spike streams for further experiments.

In our experiments, the spike camera parameters are as follows: a pixel size of $22 \mu m$, a frame rate of 20,000 fps, and a frame resolution of 400×250 pixels. The specified variables and their corresponding ground-truth parameters of the droplets in Figure 3 in the main text are summarized in Table 1.

Table 1: Specified parameters of synthetic datasets.

Experiment	d	i	k	p	v	S	f
Figure 3(a)	16	24	10	1	44	352	50
	18	22	10	1	44	396	50
	20	20	10	1	44	440	50
	22	18	10	1	44	484	50
Figure 3(b)	24	16	10	1	44	528	50
	12	8	20	1	22	264	50
	16	14	13.3333	1	33	352	50
	14	26	10	1	44	308	50
	20	30	8	1	55	440	50
Figure 3(c)	18	42	6.6667	1	66	396	50
	20	30	10	1	44	440	40
	14	26	10	1	44	308	50
	18	13	10	1	44	396	65
	16	9	10	1	44	352	80
	12	8	10	1	44	264	100

2 EVALUATION DETAILS

To compare the performance of spike-based and image-based methods, we employed error-based metrics as measurements, such as frequency error and velocity error. The following are the implementation details: For an individual set of data, We conducted parameter estimation for each method n times. The estimated parameters can be expressed as:

$$Q = \{q_1, q_2, q_3, \dots, q_n\} \quad (5)$$

where q_n represent the parameter estimation result for the n -th iteration. We then calculate the average value of the estimated parameters.

$$q_{avg} = \frac{1}{n} \sum_{i=1}^n q_i \quad (6)$$

Subsequently, the error value E can be obtained by taking the absolute difference between the estimated value and the observed value:

$$E = ||q_{avg} - q_{ob}|| \quad (7)$$

where q_{ob} is the observed value. Smaller error values imply better predictive accuracy. In Section 5.4 in the main text, we let $n = 3$. Comparing the errors between the spike-based and image-based methods in Table 1 of the main text, we observe that the former demonstrates higher predictive accuracy.

3 COMPREHENSIVE EVALUATION OF DROPLET MICROFLUIDICS

The input parameters in droplet microfluidics play a crucial role in determining droplet generation. Employing the spike-based parameter estimation approach enables accurate assessment of performance across various parameter configurations in droplet microfluidics. This method facilitates a comprehensive analysis of the overall microfluidic chip performance, laying a solid foundation for subsequent optimization efforts. In our designed microfluidic chip, water and oil are introduced separately, resulting in oil shearing water to form droplets. By delicately adjusting the pressures at both the oil and water inlets, the formation of droplets can be precisely controlled. This entire process is captured via a spike camera, with subsequent

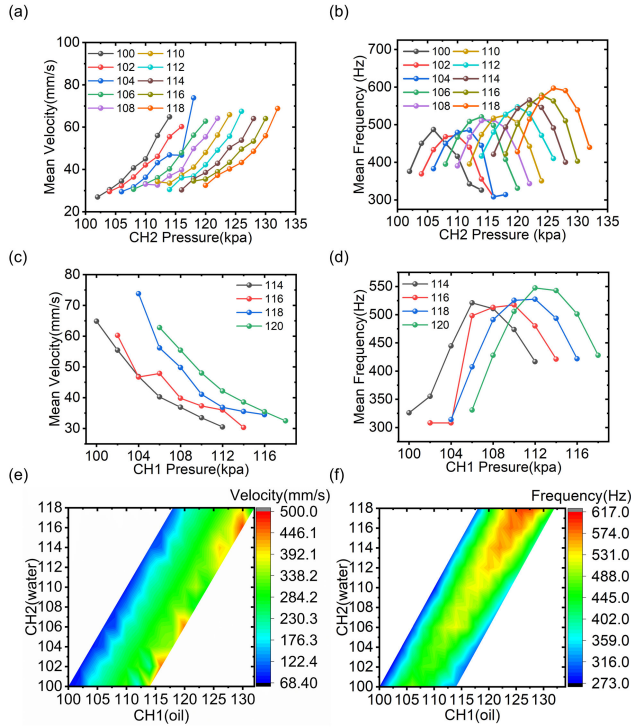


Figure 1: Comprehensive evaluation of droplet microfluidics. (a) When the oil phase is fixed, the droplet velocity varies with changes in the pressure of the water phase. (b) When the oil phase is fixed, the frequency of the droplet generation varies with changes in the pressure of the water phase. (c) When the water phase is fixed, the droplet velocity varies with changes in the pressure of the oil phase. (d) When the water phase is fixed, the frequency of the droplet generation varies with changes in the pressure of the oil phase. (e) The velocity parameter estimation heatmap. (f) The frequency parameter estimation heatmap

spike-based parameter estimation methods. As depicted in Figure 1(a), it becomes apparent that while the pressure of the oil phase remains constant, increasing the pressure of the water phase leads to a gradual increase in droplet velocity. However, the generation frequency exhibits an initial increase followed by a subsequent decrease with a rising water phase pressure, as shown in Figure 1(b). Conversely, when the pressure of the water phase is held steady, an increase in oil phase pressure results in a reduction in droplet velocity (Figure 1(c)). Correspondingly, the frequency depicts an analogous trend of an initial rise and then a subsequent decline in response to an escalation in oil phase pressure, as demonstrated in Figure 1(d). Finally, the heatmaps of droplet velocity parameter estimation using the spike-based method under different input parameters (Figure 1(e)) and the frequency parameter estimation heatmap (Figure 1(f)) offer a directional insight into the dynamic modulation of microfluidic chip performance parameters.

3.1 Spike-based method enables real-time droplet microfluidics parameter evaluation

The droplet microfluidics parameter evaluation based on spike streams is more efficient compared to the method based on reconstructed images due

to the elimination of the spike stream reconstruction process. As an end-to-end processing method, the spike-based approach exhibits higher efficiency. To compare the performance between the spike-based method and the spike reconstruction-based method, we conducted parameter evaluation on spike streams over two seconds. The calculation was performed within a window of 1 second, with a sliding step of 50 microseconds. The average computation time of each module during the sliding window process was taken as the final time consumption. It's worth noting that the reconstruction process in TFI[2] was accelerated using CUDA. The experimental platform consisted of a workstation equipped with a GTX 1080 GPU and an Intel Core i7-9700 CPU. The time consumption of various components in the spike-based parameter estimation method mostly falls within the millisecond range. Among these components, The most time-intensive part is the calculation of the droplet velocity, which is currently carried out through a Python-based process without acceleration. On the contrary, the parameter estimation method based on spike reconstruction follows a comparable calculation process to the spike-based method but necessitates the reconstruction images from the spike stream. Although efforts have been made to accelerate this reconstruction process using CUDA, it still takes seconds, a significantly longer duration than the spike-based parameter estimation approach. Compared to the spike reconstruction-based method, the end-to-end parameter estimation approach utilizing the spike stream efficiently achieves droplet parameter estimation, demonstrating the potential for real-time parameter estimation.

REFERENCES

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