Event-based Rapid Organoid Imaging

Rongzhou Chen[1], Yuxing Li[1], Chutian Wang[1], Shaohua Ma[2] and Edmund Y. Lam[1,*]

[1]*Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR*
[2]*Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen*

[*]*elam@eee.hku.hk*

Abstract: We present an integrated imaging system that combines a microfluidic platform with an event-based vision sensor to achieve rapid, low-phototoxicity imaging of organoids. Leveraging a computational neuromorphic imaging framework, our system effectively compensates for fluid-induced motion and reconstructs high-fidelity images from sparse event data.

1. Introduction

Rapid, high-resolution imaging of biological organoids is essential for applications in high-throughput drug screening and cancer research. Conventional imaging modalities often require extensive sample preparation and high illumination intensities that can induce phototoxic effects [1]. Event-based vision sensors, which capture only changes in brightness with microsecond temporal resolution and an extended dynamic range, enable low-illumination imaging [2]. In parallel, microfluidic platforms allow for precise and rapid sample manipulation, facilitating dynamic imaging conditions.

In this work, we integrate a microfluidic platform with an event-based sensor and a real-time computational neuromorphic imaging (CNI) pipeline [3]. Our approach directly predicts velocity and affine transformation parameters from segmented event streams using a deep recurrent network, thereby achieving real-time motion compensation and frame reconstruction. Building on recent advances in organoid culture techniques and analysis methods, our system offers a robust and efficient solution for high-quality, low-phototoxicity imaging of organoids [4,5].

2. Method & Results

Our imaging system processes event data through a structured pipeline with a microfluidic platform (Flugien Flow EZ) and an event camera (DAVIS 346) as shown in Figure 1. After acquisition by the event camera (Figure 1(a)), the raw events visualized in Figure 1(b) are segmented into fixed length intervals for processing. Each event, defined as $e = (t, x, y, p)$, consists of a timestamp, spatial coordinates, and polarity, which are normalized and padded for subsequent velocity prediction and motion compensation depicted in Figure 1(d).

The core of our approach employs a deep recurrent network based on a stacked long-short-term memory (LSTM) architecture (Figure 1(d)) to predict motion parameters directly from end to end. For each event segment, the network produces a velocity vector $v \in \mathbb{R}^2$ that describes the fluid-induced motion and affine transformation parameters $t = (\alpha, s_x, s_y)$, where α controls the scale and s_x, s_y denote spatial shifts. These parameters enable real-time motion compensation through coordinate warping. For each event in segment i, we compute the warped coordinates as

$$x' = x - v_x \cdot \frac{W}{T}(t - t^{\min}), \quad y' = y - v_y \cdot \frac{H}{T}(t - t^{\min}), \tag{1}$$

where W and H represent the sensor dimensions, $t^{\min}$ is the minimum timestamp in the segment, and T is the segment duration. Without this motion compensation, reconstructed images exhibit significant blur and distortion, as demonstrated in Figure 1(c).

Following motion compensation, the warped events are accumulated into a three-dimensional spatio-temporal tensor using trilinear interpolation techniques adapted from computational neuromorphic imaging principles [3]. Summing along the temporal dimension produces a two-dimensional image representing the integrated event response. To further enhance spatial detail and focus on the region containing the organoid, we apply an affine grid sampling method to extract a region of interest (ROI) based on the predicted transformation parameters depicted in Figure 1(e). The ROI is obtained by constructing an affine matrix

$$\Theta_{b,i} = \begin{bmatrix} 1/S_x & 0 & -s_x/S_x \\ 0 & 1/S_y & -s_y/S_y \end{bmatrix}, \tag{2}$$

where the scaling factors S_x and S_y are derived from α and predetermined object size limits.

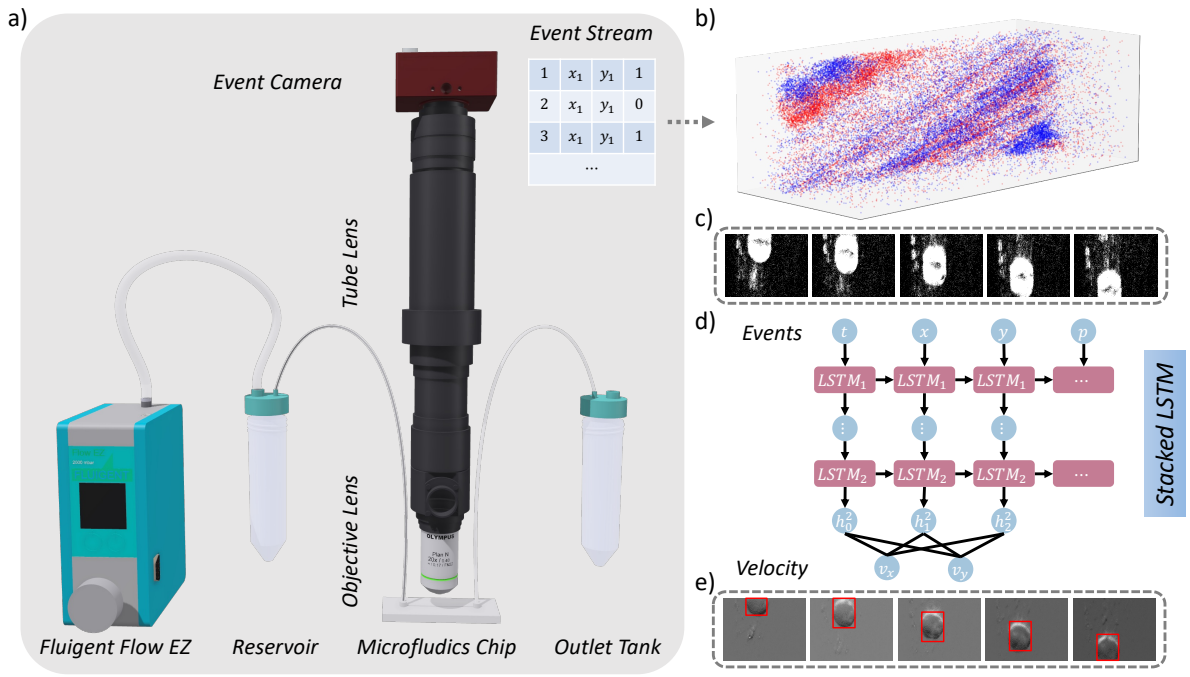

Fig. 1: Integrated event-based organoid imaging system. (a) Microfluidic platform with Fluigent Flow EZ controlling sample flow through a chip beneath the event camera. (b) 3D visualization of raw event data (red: positive, blue: negative). (c) Uncompensated event reconstructions showing motion-induced blur. (d) Stacked LSTM network architecture for real-time velocity prediction. (e) Motion-compensated reconstructions with improved clarity after velocity-based warping.

Our complete pipeline operates in a real-time loop with a training objective designed to maximize image contrast through accurate velocity prediction. We formulate this as a composite loss function

$$L = -\lambda_1 C(I) + \lambda_2 R(v) - \lambda_3 D(R) \tag{3}$$

where $C(I)$ represents image contrast, $R(v)$ is velocity regularization, and $D(R)$ measures ROI density. This optimization strategy minimizes motion blur and preserves structural details, as shown in Figure 1(e) compared to uncompensated reconstructions in Figure 1(c). Our system enables high-quality frame reconstruction under low illumination conditions, significantly reducing phototoxicity, a critical advantage for longitudinal organoid studies. The real-time performance makes this approach particularly suitable for high-throughput applications in drug screening and biomedicine [4, 5].

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