Neuromorphic Approach to Micro-Particle Tracking

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***Abstract*— The tracking and analysis of moving micro-particles is a demanding task in fields such as industrial processing and biotechnology. Traditional methods rely on conventional frame-based cameras (Charge-Coupled Device (CCD) or Complementary Metal-Oxide Semiconductor (CMOS)) and post-processing software, which often face limitations regarding data volume and processing speed as particle count or velocity increases. This paper explores a neuromorphic approach using event-driven vision sensors, specifically Dynamic Vision Sensors (DVS) and Selective-Change-Driven (SCD) sensors. Unlike traditional systems, these sensors detect local changes in luminance asynchronously, providing high temporal resolution with significantly lower data flow. We present preliminary evidence of micro-particle tracking using several non-commercial, home-developed event-driven cameras integrated into a microfluidic experimental setup.**

Keywords*- *Selective-Change-Driven (SCD); Dynamic Vision Sensor (DVS); microfluidic; Particle Image Velocimetry (PIV); Particle Tracking Velocimetry (PTV).

I. Introduction

The tracking and analysis of moving micro-particles is a demanding task in fields as diverse as industrial processing and biotechnological activities. The classical approach relies on conventional frame-based cameras (CCD or CMOS) and post-processing software to perform Particle Tracking Velocimetry (PTV) or Particle Image Velocimetry (PIV) [1][2]. Recently, these methods have been adapted for microfluidic applications such as Microparticle Tracking Velocimetry (uPTV) [3] and Microparticle Image Velocimetry (uPIV) [4] using time-lapse microscopy. Microfluidic systems rely on diverse microfabrication techniques (such as semiconductor processing, micro-machining and additive manufacturing) [5] to create micrometer-scale structures. For basic microchannel studies, particles are injected using a syringe pump and monitored via a microscope coupled with a camera, although future diagnostic applications aim for fully integrated, compact systems.

To overcome the limitations of actual µPTV/µPIV algorithms (such as high computational cost and noise sensitivity) various Artificial Neural Network (ANN) algorithms [6] are increasingly used. Applications range from stereoscopic tracking velocimetry using Stochastic Neural Network (StochNN) [7] and Convolutional Neural Network (CNN) have been used in particle identification [8] to unsupervised feature extraction [9]. In any case, as the number or speed of tracked particles increases, various limitations arise, both in terms of detection (streaks and shadows in images) and processing (given the large amount of data generated), suggesting the use of more powerful approaches, such as those based on new event-based vision sensors [10].

Since the first attempt to replicate human vision in silicon [11], neuromorphic vision sensors (also called Event-Driven, ED) have demonstrated their enormous potential to outperform traditional frame-based systems in terms of energy, resources, and processing speed [12]. These advantages are especially important in fields where high processing speed and very high data rates are required, such as unmanned aerial vehicle (drone/UAV) guidance [13] or multiple particle tracking [14]. While several ED sensor families exist, DVS are currently the most industrial mature [10][15][16]. DVS detect local luminance changes asynchronously as events rather than frames, providing microsecond latency, high dynamic range and low data flow. A specific variant is the SCD sensor [17][18], which uses a Winner-Take-All (WTA) circuit [19] to output the coordinates and intensity of the most significant changes on demand. At 128×128 resolution, SCD sensors offer latencies as low as $100\,\mathrm{ns}$, making them ideal for high-speed tracking.

Event-based sensors offer three key advantages:

- Asynchronous event detections, which reduces bandwidth up to 100 times compared to conventional cameras while maintaining microsecond resolution [14][20]–[22].
- Real-time processing, enabling long-duration recordings and faster-than-real-time analysis without memory constraints [14][22].
- Robustness and flexibility, providing high dynamic range and tolerance to variable illumination in brightfield, fluorescence or high-velocity environments [20]–[22].

In this paper, we present preliminary evidence of the utilization of several non-commercial event-driven cameras for micro-particle tracking applications. The structure of the paper is as follows. In Section II, we specify the experimental setup, explaining the microfluidic components besides the specific architectures of SCD and DVS cameras used in this work. In Section III, we present and analyze the preliminary results obtained from capturing high-speed microparticle fluid. Finally, the conclusions and future work are presented in Section IV.

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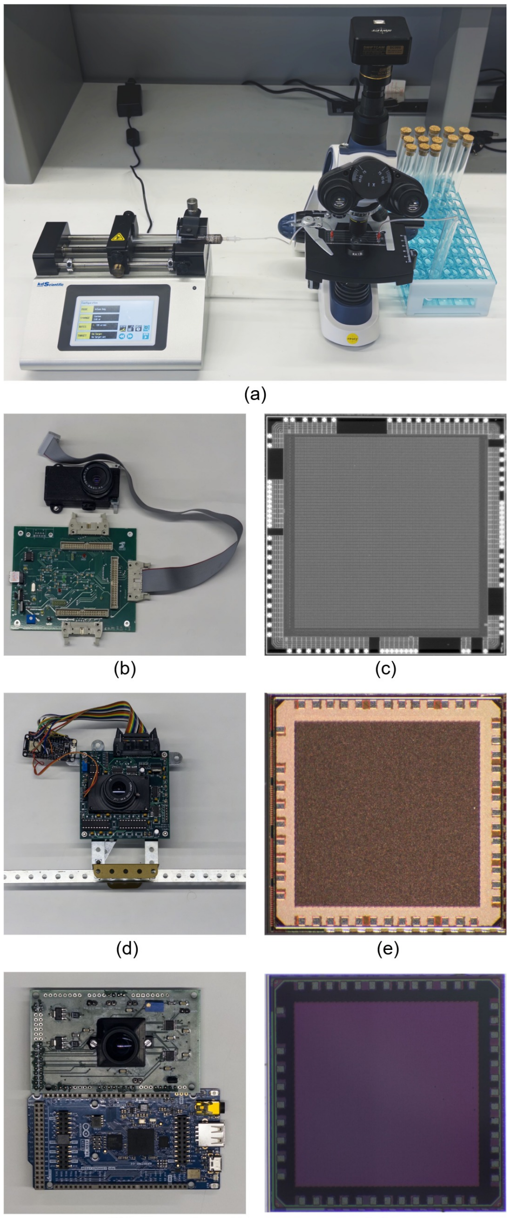

Figure 1. ED cameras and sensors considered in this study: (a) Experimental setup; (b)-(c) DVS camera and sensor; (d)-(e) SCD camera and sensor (64×64); (f)-(g) SCD camera and sensor (128×128).

II. Experimental setup

A complete experimental setup, comprising a standard microscope and a laboratory-grade syringe pump. We made use of Commercial Off-The-Shelf (COTS) single-channel microfluidic chips, and commercial microparticles were considered. To validate our proposal, we utilized home-developed SCD cameras, which were compared to a DVS camera. A conventional digital camera was used as a reference.

A. Microfluidics setup

The utilized setup is shown in Figure 1 (a). As a pump we used the KD Scientific Legato 110 which is a high-precision, single-syringe infusion and withdrawal with a volumetric accuracy of $\pm 0.5\%$ capable of hosting a broad range of syringe volumes from 0.5 μL to 60 mL, an wide range of flow rates, from less than 2 pL/min up to more than 50 mL/min. Fluidic experiments were conducted using a multi-channel thermoplastic chip (Fluidic 138, microfluidic ChipShop GmbH, Jena, Germany). The device comprises four independent straight channels, each measuring 58.5 mm in length with a cross-section of 1000 μm $\times$ 200 μm. Fluidic access was achieved via integrated Mini Luer ports, and the optical transparency of the [Polimethyl methacrylate (PMMA)/Topas] substrate permitted real-time visualization of the flow dynamics. Flow visualization was performed using fluorescent silica particles (sicastar®-redF, micromod Partikeltechnologie GmbH, Rostock, Germany) with a nominal diameter of 20 μm.

B. DVS camera

This camera is based on a 128×128 pixels DVS with improved sensitivity [23]. Each pixel in the DVS sensor individually responds to relative temporal variations of the illumination inpinging on it [24] generating asynchrounously a signed output address event when the relative variation in the illumination goes over a controllable threshold. The output address event codes the (x,y) address that identifies the pixel generating the event. An additional sign bit codes the direction (increasing or decreasing) of the illumination variation. In the sensitive DVS, a low-power low-mismatch amplification stage is added to each pixel which enables the detection of low illumination contrasts [25], making the sensor able to achieve the low noise high sensitivity conditions needed for microscopic applications.

C. SCD camera (64×64 pixels)

This camera is based on a 64×64 SCD vision sensor implemented in standard TSMC 180 nm CMOS technology [17]. It uses a continuous-time logarithmic photoreceptor and a high-speed WTA circuit to select the pixel with the greatest illumination change. The sensor delivers pixels ordered by the illumination change since they were last read, allowing for reduced data bandwidth without loss of accuracy. The sensor can operate in both SCD mode, where it selects and outputs the most changed pixels, and conventional frame-based mode. Compared to frame-based cameras, the SCD sensor can detect and track very fast-moving objects, up to 5-10 kHz, with the same time resolution for both events and illumination level.

D. SCD camera (128×128 pixels)

The sensor of this camera is a recently developed evolution of the previous one. In this case, it is implemented in standard TSMC 65 nm CMOS technology. It includes all the aforementioned characteristics, plus a double parallel WTA circuit, managing ON and OFF events. Preliminary mesurements have also evidenced its higher velocity. Frames from a standard camera are also included as a reference.

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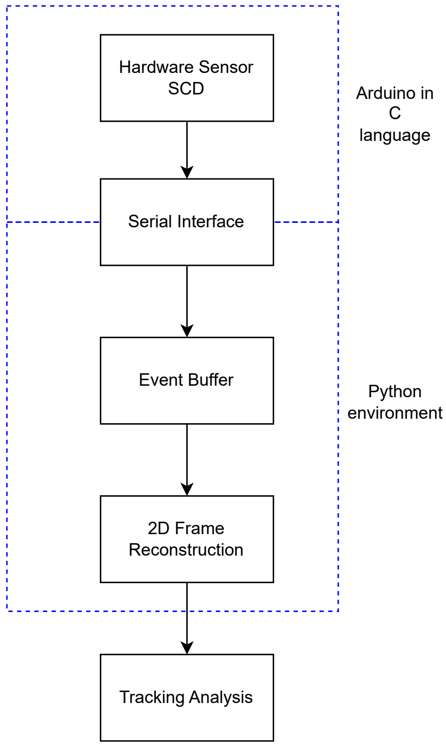

Figure 2. Flowchart describing the method for event processing.

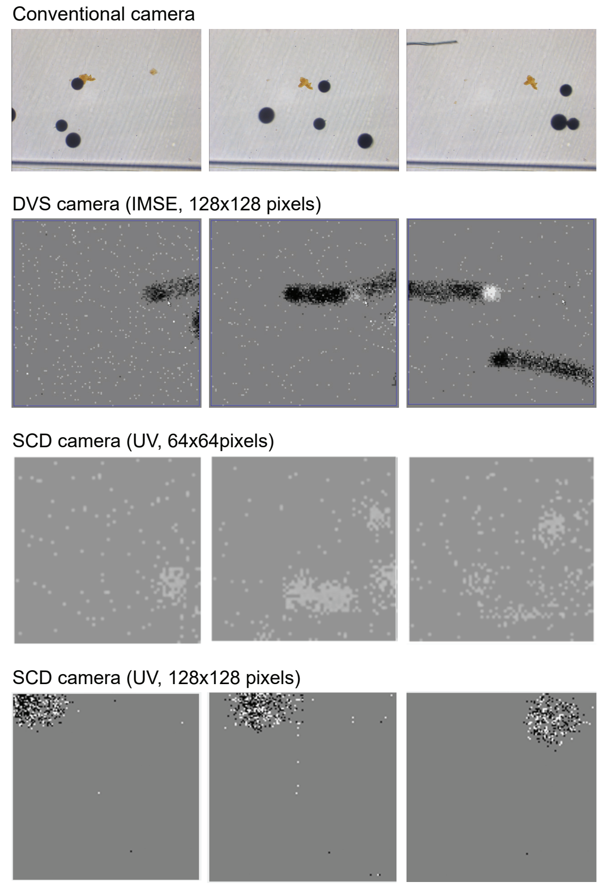

Figure 3. Events captured as frames, for better presentation.

E. Data Processing and Tracking Method

To process the data generated by the neuromorphic sensors, a real-time event-to-frame conversion pipeline is needed. For SCD cameras, the pipeline was implemented using Python as shown in Figure 2 instead of DVS cameras that uses an open-source tool called jAER viewer. Unlike conventional cameras that require high-bandwidth interfaces such as USB 2.0 or 3.0 to transmit full frames, the SCD sensors transmit event data via a standard serial port connection.

Inside the Python environment, the incoming serial event stream is buffered to reconstruct 2D frames in real-time as shown in Figure 3. Once the events are mapped into images, frame-based particle tracking methods are applied to estimate the average fluid velocity. This hardware-software design allows the system to use robust tracking algorithms while fully exploiting the sensor advantages such as high resolution and a drastic reduction in data transmission bandwidth at the hardware level.

III. Preliminary results

We have attached the different cameras to the microscope, while maintaining an average fluid velocity of about 1.33 mm/s. Results are collected in Figure 3. As observed, the flowing particles are tracked in any case.

To facilitate the visualization and qualitative comparison of results, we have extracted frames from the events reconstruction of all cameras. As shown in Figure 3, the conventional camera is provided as a baseline reference. The camera captures the particles flow correctly, however, for a 1.33 mm/s flow, the sensor generates massive amounts of redundant data for the static microchannel background.

In contrast, the DVS camera demonstrates an advantage in extracting purely movement information. Because the DVS camera only records local temporal changes in illumination, the static background is suppressed. Figure 3 illustrates the resulting output as discrete events corresponding exactly to the particles movement. The contrast changes are precisely illustrated, mapping out high-resolution trajectory paths without the heavy data overhead of synchronous full-frame readout.

Finally, both variants of SCD sensors proved highly efficiency for high-speed micro-particle tracking under real experimental conditions. The 64×64 SCD camera successfully tracked the flow, validating the efficacy of the continuous-time logarithmic photoreceptor and WTA pixel selection despite the lower resolution. The upgraded 128×128 SCD camera obtained a markedly better spatial detail, effectively capturing the flow with minimal noise. Overall, these results verify that neuromorphic architectures can isolate high-speed moving tar-

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gets from static backgrounds at the microscope scale producing low amount of data but rich in movement information perfectly appropriated for next-generation velocimetry algorithms.

IV. Conclusion and Future Work

This study demonstrates the viability of utilizing non-commercial event-driven cameras for micro-particle tracking applications. By integrating these sensors with a standard microscope and a microfluidic system, we successfully tracked flowing particles at an average fluid velocity of approximately 1.33 mm/s. Further experiments are required to quantify the performance of each camera.

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