MOMS with Events:  
Multi-Object Motion Segmentation With Monocular Event Cameras

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Abstract. Segmentation of moving objects in dynamic scenes is a key process in scene understanding for both navigation and video recognition tasks. Without prior knowledge of the object structure and motion, the problem is very challenging due to the plethora of motion parameters to be estimated while being agnostic to motion blur and occlusions. Event sensors, because of their high temporal resolution, and lack of motion blur, seem well suited for addressing this problem. We propose a solution to multi-object motion segmentation using a combination of classical optimization methods along with deep learning and does not require prior knowledge of the 3D motion and the number and structure of objects. Using the events within a time-interval, the method estimates and compensates for the global rigid motion. Then it segments the scene into multiple motions by iteratively fitting and merging models using as input tracked feature regions via alignment based on temporal gradients and contrast measures. The approach was successfully evaluated on both challenging real-world and synthetic scenarios from the EV-IMO, EED and MOD datasets and outperforms the state-of-the-art detection rate by as much as 12% achieving a new state-of-the-art average detection rate of 77.06%, 94.2% and 82.35% on the aforementioned datasets.

Keywords: Motion and Tracking, Vision for Robotics, Deep Learning: Applications, Methodology, and Theory, Scene Understanding, Segmentation, Grouping and Shape

1 Introduction

Motion is the evolutionary most basic cue for visual perception and allows for computing scene geometry [12][34]. Even, though there have been tremendous advances in the area of visual navigation, usually addressed through structure from motion and SLAM [19], state-of-the art approaches are still limited in that they are designed for static scenes, or specific moving objects known in advance. Inspired by the motion processing of mammalian vision, neuromorphic engineers have developed a sensor called silicon retina or DVS (dynamic vision sensor), that mimics the transient signal. This event-based sensor does not record
image frames, but asynchronous temporal changes in the scene in the form of a stream of events. The sensor gives unparalleled advantage in-terms of temporal resolution, low latency, and low band-width signals. It appears that the data from DVS provides valuable information for motion segmentation, because of the high density of events at object boundaries, and lack of motion blur and occlusions.

One of the most challenging problems in visual navigation is the problem of multi-motion segmentation in dynamic scenarios. The first step in solving this complex problem is finding the Independently Moving Objects (IMOs) while also estimating self-motion/ego-motion. Researchers have relied on computing optical flow as a first step in solving visual navigation tasks. However, computing accurate optical flow is not trivial and does not work well in dynamic scenarios due to discontinuities and occlusions from the moving objects. To obtain accurate optical flow, one has to detect the IMOs, and remove them from the scene. Then the optical flow from the static scene could be used to compute ego-motion. However, to detect the IMOs ego-motion is necessary. Thus, ego-motion estimation and IMO detection and estimation are chicken-and-egg problems: you need the solution of one to solve the other [33]. This paves the path for a joint optimization to solve for camera ego-motion and IMO motion.

In this work, we solve this joint optimization problem with a blend of top-down and bottom-up approaches. Given the events within a time-interval, we start the algorithm by utilizing a top-down approach to fit a global parametric motion model to the event stream which is then motion-compensated. We then track sparse features and cluster the features using K-means clustering. Subsequently clusters are merged by fitting a four-parameter motion model to the movement of features. The process is iterated until a stopping criterion is reached.
The result of this pipeline is a set of regions denoting separately moving rigid bodies – the information which can be used for further segmentation or 3D pose estimation. The main contributions of our work can be summarized as:

1. A novel iterative model fitting and merging approach for monocular multi-object motion segmentation, without any prior knowledge (e.g. 3D motion, scene geometry, number of objects).
2. The first approach to combine event-based feature tracking and flow via event alignment (to combine sparse and dense image motion information)
3. A thorough evaluation on both synthetic and challenging real-world scenarios, outperforming the state-of-the-art.

2 Related Work

2.1 Event-based Flow, Feature Tracking, and 3D Motion Estimation

Event cameras are ideal for capturing instantaneous image motion. Since events are recorded at high contrast locations, the data carries potentially useful information for obtaining optical flow at boundaries. Early approaches implemented correlation and bio-inspired mechanisms. Delbruck [10] locates linear spatial structures via an event-based orientation filter and then searches for matching event patterns within a window. Liu and Delbruck [22] provide an efficient FPGA implementation of a block matching mechanism. Conradt [9] demonstrated a Reichardt detector like-model in FPGA, and Haessig et al [16] a neural network inspired by the Barlow Levick model on a TrueNorth chip. The first gradient-based technique, using as input a slice of accumulated events, was proposed in [6]. To overcome the difficulties due to the inherent ambiguity in the local event information, [2] accumulate events over longer time intervals in a gradient based approach. In the most adapted flow technique [5], the local component of motion (normal flow) is obtained by fitting via PCA a plane to time-stamps in local spatial neighborhoods, which are then combined into optical flow using least squares fitting. Orchard et al. [30] implement a similar fitting with a network, and Mueggler et al. [27] adapt the approach using a causal filter. Finally, energy filters defined on accumulated events were proposed in [7,38], and Barranco et al. [3] showed that by using the phase, accurate estimates can be obtained in textured regions.

Zhu et al. [42] proposed the first self-supervised learning algorithm for optical flow estimation, but using gray-scale information to define the loss function for supervision. Ye et al. [41] trained the first unsupervised network using only events to obtain flow, depth, and 3D motion, and Mitrokhin et al. [25] combined supervised and unsupervised network components for flow estimation, 3D motion, and object segmentation.

A number of event-based feature detectors and trackers have been proposed. Clady et al. [8] compute corner features by intersecting local time surfaces to which they fit planes, and they match them over time. Vacso et al. [39] adapt the Harris corner detector to event time data. Tedaldi et al. [37] detect corners
in the gray-level image (from the DAVIS camera) using the Harris detector and track them by registering events. Mueggler et al. [26], inspired by the FAST detector [32], created a detector that responds when a certain amount of points within a circular spatial neighborhood of the time surface have been activated. Alzugaray and Chli [1] introduce a reference time into the this feature, to provide a much faster detection and tracking that asynchronously operates on the event stream.

The features have been used in 3D motion estimation approaches using visual odometry or SLAM formulations, for rotational motion only [31], known maps [40,14], and in combination with IMU sensors [42]. Other recent approaches jointly reconstruct the image intensity of the scene, and estimate 3D motion [17,18].

### 2.2 Motion Segmentation in Event-based Vision

Event-based motion segmentation has been addressed over the past decade for different scenarios at variable scene complexity. The most simple scenario is the static camera case, because the events are generated only by moving objects, and the segmentation problem reduces to event clustering [21,20,23,4]. On the other hand, the more complicated scenario is that of a moving camera. In such case, events are generated from both ego-motion (camera motion) and moving objects, and to separate them, the camera motion and possibly even information about the structure must be estimated [29]. Recently, motion segmentation for moving cameras has been addressed using the concept of motion-compensation. The idea is to shift all events within a time slice to the the beginning of the time interval, and in this way all events in the transformed event cloud, when projected onto an image should align on high contrast contours. The alignment can be evaluated using different measures of dispersion [15,42,24] or sharpness [13,36]. Mitrokhin et al. [24] detect moving objects by fitting a four parameter motion model to the background and grouped misaligned regions into segments. Then, the Kalman filter is used to track moving objects to handle occlusions and uncertainty in the scene efficiently. Even though, the approach was demonstrated under very challenging scenarios such as high dynamic range, and high speed motion, since the segmentation itself is a simple thresholding based grouping mechanism, the algorithm cannot handle multiple objects of different motion. Stoffregen et al. [35] extended the technique by adding an Expectation-Maximization(EM) based segmentation algorithm, showing excellent results for simultaneous segmentation and optical flow estimation. However, the EM approach requires the clusters to be initialized with knowledge of the number of moving objects in the scene. Our paper aims at solving the limitations of these prior event-based motion segmentation techniques, by introducing into the pipeline a much better segmentation module based on feature tracking. It can handle multiple objects with different motions, and does not require assumptions on the number of moving objects in the scene.
3 Methodology

3.1 Event Camera

A traditional camera records frames at a fixed frame rate by integrating the number of photons for the chosen shutter time for all pixels synchronously. In contrast, an event camera only records the polarity of logarithmic brightness changes asynchronously at each pixel. If the brightness at time $t$ of a pixel at location $\mathbf{x}$ is given by $I_{t,\mathbf{x}}$, an event is triggered when $\| \log (I_{t+\delta t,\mathbf{x}}) - \log (I_{t,\mathbf{x}}) \|_1 \geq \tau$. Here, $\delta t$ is an infinitesimal small time increment and $\tau$ is a threshold which will determine the trigger of an event ($\tau$ is set at the driver level as a combination of multiple parameters; by default it is set to 0.1). Each triggered event outputs the following data: $e = \{\mathbf{x}, t, p\}$, where $p = \pm 1$ denotes the sign of the brightness change. We’ll denote events in a spatio-temporal window as $\mathcal{E} = \{e_i\}_{i=1}^N$ ($N$ is the number of events) and we’ll refer to $\mathcal{E}$ as event slice/stream/cloud/volume.

3.2 Problem Statement

The specific question we answer is as follows: How do you cluster the scene into background and IMOs without a prior of object shape, size, structure and number of objects?

Given an event volume $\mathcal{E}$, we find and cluster the events based on 2D motion. Each cluster is represented by a four parameter model (denoting the similarity transformation/warp) $\Theta = \{\Theta_x, \Theta_y, \Theta_z, \Theta_\theta\}$ which represents the 2D translation, divergence and in-plane rotation, respectively. In contrast to previous approaches, we do not need the prior knowledge of $K$ or a bound on it [35]. We make the following assumptions:

1. The magnitude of IMO motion is slightly larger than the ego-motion.
2. Ego-motion is not dominated by rotation.

3.3 Overview of Proposed Solution

The proposed approach combines top-down and bottom-up processing, and is summarized in Algorithm 1 and illustrated in Fig. 2.

The first step in our approach is to fit a global four parameter model directly adapted from [24]. We briefly describe this approach next.

3.4 Global Model Fitting

This step aligns the input event cloud $\mathcal{E}$ by minimizing temporal gradients $\nabla T$ where $T(\mathcal{E}) = \mathbb{E}(t_\mathbf{x} - t_0)$[24], $\mathbb{E}$ is the expectation/averaging operator, $t_\mathbf{x}$ denotes the time value at location $\mathbf{x}$ and $t_0$ is the initial time of the temporal window. We are solving the following optimization problem: $\arg\min_\Theta \| \nabla T \|_2$, ($\nabla$ denotes the spatial gradient operator). This estimates the warp parameters $\Theta$ which maximizes the contrast or sharpness, thereby minimizing the temporal gradients.
3.5 Residual Motion Tracker

Once the event cloud $\mathcal{E}$ is warped using $\Theta$ and then projected onto the 2 dimensional image plane, we obtain a motion compensated image $\mathcal{E}$ which is sharp on the background boundaries and “blurry” on the object boundaries (denoting the inconsistency in the motion model between the background and IMOs). Grouping these inconsistencies is not trivial and requires local motion information. Hence, we employ a sparse feature detection and tracking approach to gather local information and group residual motion. Over the past few years, robust feature extraction and tracking approaches for event data have been proposed. We found deep learning-based approaches to be more robust and generalizable over a wide range of scenarios without data fine tuning. Hence, we utilize the approach of DeTone et al. [11] (previously used on gray-level images) for extracting sparse features $\mathcal{F}$ from $\mathcal{E}$.

3.6 Iterative Model Fitting And Merging

The approach consists of five steps, which are described next and summarized in Algorithm 1 and Fig. 2a.

Cluster Initialization: The first step is to group features based on motion. We employ a simple K-means clustering to cluster the feature tracks (commonly

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![Diagram](image)

**Fig. 2.** (a) Overview of the proposed approach, our contributions are highlighted in yellow. The input to our system is the raw event stream $\mathcal{E}$ and the output are the motion models $\Theta$ and motion clusters $S$. (b) Projection of the raw event cloud $\mathcal{E}$ without motion compensation. (c) Projection of event cloud after global motion compensation. (d) Sparse features $\mathcal{F}$ extracted on compensated event cloud. (e) Merged feature clusters based on contrast and distance metrics. (f) Output of the pipeline is the cluster of events.
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called tracklets) based on the length of the tracks. We use five consecutive projection images $E$ to compute the tracklets ($F$). Then, we over-segment the tracklets into $K$ clusters ($K >>$ Num. of objects). If a prior on the number of objects or a bound is known, it can be trivially incorporated to choose $K$.

**Cluster-Based Model Fitting:** Next, we consider the event volume $\delta E_{ik}$ around the $k^{th}$ cluster and $i^{th}$ feature in that cluster. We then compute the fourparameter motion model (similar to the global model fitting, but centered on the cluster centroid and only considering the spatio-temporal event volume of the feature tracks) for all the event volumes in each cluster, which involves solving the following optimization problem: $\arg\min_{\Theta_k} \| \nabla T(\bigcup \delta E_k^i) \|_2$. Let us now denote the obtained model for cluster $k$ as $\Theta_k$. Since, we have an over-segmentation (each cluster is a segment) of the scene, we need to merge similar clusters, which is described next.

**Merging criterion:** Clusters will be merged based on a similarity measure that depends on the contrast match (applying the motion model of the current cluster to another cluster and measuring the contrast) and distance between centroids of the clusters. We define contrast and distance functions $C_{k,j}$ and $D_{k,j}$ respectively as follows: $C_{k,j} = \mathbb{E}(\|\text{Var}(E(\delta E_j|\Theta_k))\|_1)$ and $D_{k,j} = \| C_k - C_j \|_2$ where $E$ denotes motion compensated image after the warping and projection operation, $k, j$ are the cluster numbers and $C_k$ denotes the centroid of cluster $k$. This formally entails solving the following optimization problem: $\arg\max_j C_{k,j} D^{-1}_{k,j}$ which simultaneously maximizes the contrast and minimizes the distance. This step is iteratively performed per cluster (where merging happens with every neighboring cluster using breath first search) until a stopping criterion has been reached. The entire process is repeated until all the clusters have been visited.

**Stopping criterion:** After each merging operation, we compute motion model $\Theta_{k,j}$ of the merged clusters by minimizing the temporal gradients $\nabla T$. Intuitively, when two clusters are merged, the combined motion model captures the average motion present in the two clusters thereby slightly increasing the average temporal gradients of the scene. Further, whenever a moving object cluster is merged with the background cluster the average temporal gradient increases drastically. Hence, a difference in temporal gradient at every step $i$ ($\mathbb{E}(\|\nabla T_i\|_2)$) with respect to the initial step ($\mathbb{E}(\|\nabla T_0\|_2)$) is computed. If at any step the difference in temporal gradient is large, we terminate the current merging and continue to the next iteration until all the clusters have been visited. This is shown in Fig. 3 and mathematically described by $\| \mathbb{E}(\|\nabla T_i\|_2) - \mathbb{E}(\|\nabla T_0\|_2) \|_1 \geq \lambda$, where $\lambda$ is a user chosen threshold.

**Final Event Clusters:** The output of the iterative model fitting and merging step is a set of feature clusters and corresponding motion models. We obtain the dense segmentation by taking the convex hull of the sparse feature points in each cluster, which is denoted as $S$. 
Algorithm 1: Multi-object Motion Segmentation

|   |   |
|---|---|
| **Input:** \( \mathcal{E} \)  | \( \Theta, S \)  |
| **Output:** \( \Theta, S \)  | \( \mathcal{E}, \Theta_0 = \text{GlobalModelFitting}(\mathcal{E}) \)  |
| 1  | \( \mathcal{E}, \Theta_0 = \text{GlobalModelFitting}(\mathcal{E}) \)  | \( \mathcal{E}, \Theta_0 = \text{GlobalModelFitting}(\mathcal{E}) \)  |
| 2  | \( \mathcal{f} = \text{ResidualMotionTracker}(\mathcal{E}) \)  | \( \mathcal{f} = \text{ResidualMotionTracker}(\mathcal{E}) \)  |
| 3  | \( S_0 = \text{ClusterInit}(\mathcal{f}) \)  | \( S_0 = \text{ClusterInit}(\mathcal{f}) \)  |
| 4  | \( \Theta = \text{ClusterModelFit}(\mathcal{E}, S_0) \)  | \( \Theta = \text{ClusterModelFit}(\mathcal{E}, S_0) \)  |
| 5  | while Stopping Criterion and All Nodes Visited do  |  |
| 6  | if Merging Criterion then  |  |
| 7  | \( S_i, \Theta = \text{MergeClusters}(\mathcal{E}, S_{i-1}, \Theta) \)  | \( S_i, \Theta = \text{MergeClusters}(\mathcal{E}, S_{i-1}, \Theta) \)  |
| 8  | end  | end  |
| 9  |  |  |
| 10 | \( S = \text{ConvexHull}(S_i, \mathcal{f}) \)  | \( S = \text{ConvexHull}(S_i, \mathcal{f}) \)  |

4 Experiments and Results

We evaluate our approach on publicly available real and synthetic datasets. We demonstrate our approach’s performance both qualitatively and quantitatively employing two different metrics based on the availability of groundtruth information.

4.1 Overview of Datasets

**EV-IMO**[25] is a real-world dataset which contains five backgrounds namely box, floor, table, tabletop and wall of different size, shape and colored IMOs. The sequences capture the motion of objects moving in random trajectories and of varying velocities, and they have been collected using the DAVIS 346 camera. It is one of the most challenging open-source datasets for IMO segmentation as the evaluation on this dataset pushes the limits of feature tracking methods. We limit our evaluation to the sequences box and wall, for which the objects are moving faster than the camera and the background.
Fig. 4. Qualitative Evaluation of our proposed segmentation approach on three datasets. Top two rows: EV-IMO dataset, Middle two rows: EED dataset, and Bottom two rows: MOD dataset. Insets show the corresponding grayscale/RGB images for reference. The gray events represent the background cluster, and colored events represent different objects. Bounding boxes in the images are color coded with respect to the objects for reference. All the outputs are generated with the same value of $\lambda$. 
Extreme Event Dataset (EED) [24] is also a real-world event dataset which was captured using DAVIS240B under two different scenarios. The two scenarios primarily differ in the way how the camera is moved during the collection. In one scenario the sensor is mounted on a quadrotor and in the second scenario the camera is hand-held, which introduces a variety of camera motions in the data. Several frames have fast moving and multiple objects with varying shapes under different lighting conditions. Evaluation on EED demonstrates the robustness of our approach with respect to changes in illumination and different motion types.

Moving Object Dataset (MOD) [33] is a synthetic event dataset generated with the simulator of [28], specifically targeted to learning based approaches. In order to facilitate domain adaptation the data varies significantly in shape, texture and trajectories. The wall textures, objects and the object/camera trajectories have been randomized so to obtain seven different configurations. In each setup there are three objects of different shape, size and color, and the images are generated with a rate of 1000 frames per second. Each frame has a resolution of $346 \times 260$ which are then used to generate an event cloud as proposed in [33].

4.2 Detection Rate

For datasets which provide timestamped bounding boxes for the objects, we consider the prediction as success when the estimated bounding box fulfills two conditions; (1) it has a overlap of more than atleast 50% with the groundtruth bounding box, (2) the area of intersection with the groundtruth box is higher than the intersection with outside area. We can formulate the metric as:

$$\text{Success if } D \cap G > 0.5 \text{ and } (D \cap G) > (G \cap \neg D)$$

We evaluate our pipeline’s performance on all the three datasets using this metric. We obtain the bounding box for our method by obtaining the convex hull on the cluster of events. For comparison purpose we evaluate the performance of [24] using the same metric on all the three datasets. Since [35] does not have publicly available code we could not evaluate the performance for the MOD and EV-IMO dataset. For datasets with more than one sequence, we compute the average of each model’s performance on individual sequences.

4.3 Intersection Over Union (IoU)

IoU is one the most common and henceforth the most standard measure to evaluate and compare the performance of different segmentation methods. We threshold the IoU to 0.5 for inference purposes. IoU can be formulated as:

$$IoU = \frac{D \cap G}{D \cup G}$$
where $\mathcal{D}$ is the predicted mask and $\mathcal{G}$ is the groundtruth mask. Our method outputs a cluster of events which are associated with an object. For the purpose of comparison we convert the sparse mask to a dense mask by assigning all the points lying inside the cluster as the same value. Among all the datasets available, we believe that EV-IMO dataset is the most challenging. Hence, we consider to compare our other approaches with our approaches on EV-IMO.

4.4 Discussion of Results

Table 1 reports the result of our method in comparison with two state-of-the-art IMO detection methods [24], [35] using only a monocular event camera. Our method outperforms the previous methods by up to $\sim 12\%$ detection rate which might be critical on applications. Specifically, we outperform [24] by large margin (from 5.2% to 12.3%) on all the three datasets. Also, we perform comparably with [35] on the EED dataset, even without knowing the number of moving objects, which proves the robustness of our approach in merging clusters.

Table 2 reports the comparison with [25] and [33] on the IoU metric. We clearly outperform the deep learning based approach [33] by a significant margin of approximately 9% on the EV-IMO dataset. Note that, [33] was trained on the MOD dataset and is being tested here on the EV-IMO dataset without any fine-tuning. Also, [25] was trained on the EV-IMO dataset and barely outperforms our approach when using a single value of $\lambda$ for all sequences. However, we outperform [25] by a significant margin of 9% when the value of $\lambda$ is carefully chosen for each sequence. This highlights a drawback of our approach. Currently the value of $\lambda$ has to be carefully chosen, and we leave the automatic selection of $\lambda$ to the scope for future work.

Fig. 4 shows qualitative results of our approach on all the three datasets (top two rows show results for the EV-IMO dataset, middle two rows show results for the EED dataset, and last two rows show results for the MOD dataset). Gray areas in the event images show the background cluster and red/blue colored regions show the differently segmented IMOs. Notice that we obtain a good segmentation across different scenes even when the same value of $\lambda$ is used. The outputs show the robustness of our approach to shape, size and speed of the objects and in-variance with respect to camera motion. Also, note that the objects are sometimes very hard to detect in the corresponding grayscale/RGB frames in Fig. 4 motivating the use of event cameras for IMO detection using motion cues.

|       | EED  | MOD  | EV-IMO |
|-------|------|------|--------|
| Mitrokhin [24] | 88.93 | 70.12 | 64.79 |
| Stoffregen [35] | 93.17 | -    | -     |
| Ours       | **94.2** | **82.35** | **77.06** |

Table 1. Comparison with state-of-the-art using the average detection rate [24] of moving objects (in %)
Our approach takes $\sim 20$ ms for the global model fitting, $\sim 13$ ms for feature extraction and tracking and $\sim 30$ ms for iterative model fitting and merging on a single thread i7 CPU and NVIDIA Titan Xp for feature extraction and tracking. All the clusters can be parallelly processed on a GPU which can provide a significant speed-up and we leave this in the scope for future work.

5 Conclusions and Future Work

We presented a novel iterative model fitting and merging approach for monocular multi-object motion segmentation without any prior information on the number of objects or structure of the objects and/or scene. To our knowledge, this is the first approach for monocular independent motion segmentation without aforementioned prior information and to combine bottom-up feature tracking and top-down motion compensation into a unified pipeline. A comprehensive qualitative and quantitative evaluation is provided on three challenging event motion segmentation datasets, namely, EV-IMO, EED and MOD showcasing the robustness of our approach. Our method outperforms the previous state-of-the-art approaches by up to $\sim 12\%$ detection, thereby achieving the new state-of-the-art on the three aforementioned datasets. As a parting thought, we leave the automatic choice of $\lambda$ and speeding-up our approach using deep learning and GPU accelerations to enable usage on mobile robots in the scope for future work.

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