Real-Time Pose Estimation for Event Cameras with Stacked Spatial LSTM Networks

Anh Nguyen¹, Thanh-Toan Do², Darwin G. Caldwell¹, and Nikos G. Tsagarakis¹

Abstract—We present a new method to estimate the 6DOF pose of the event camera solely based on the event stream. Our method first creates the event image from a list of events that occurs in a very short time interval, then a Stacked Spatial LSTM Network (SP-LSTM) is used to learn and estimate the camera pose. Our SP-LSTM comprises a CNN to learn deep features from the event images and a stack of LSTM to learn spatial dependencies in the image features space. We show that the spatial dependency plays an important role in the pose estimation task and the SP-LSTM can effectively learn that information. The experimental results on the public dataset show that our approach outperforms recent methods by a substantial margin. Overall, our proposed method reduces about 6 times the position error and 3 times the orientation error over the state of the art. The source code and trained models will be released.

I. INTRODUCTION

Inspired by human’s vision capability, the event camera asynchronously captures an event whenever there is a brightness change in the scene [1]. An event is simply composed of a pixel coordinate and a binary polarity value that denotes the increasing or decreasing of the local brightness. This is contrary to the frame-based camera where an entire image is acquired at a fixed time interval. Based on its novel design concept, the event camera can stream events at microsecond speed. This is superior in comparison with the frame-based camera which usually can only sample an image at millisecond rate [2]. This ability makes event cameras more suitable for high-speed applications in robotics that require low latency and high dynamic range from the visual data.

Although the event camera opens a new paradigm shift to solve real-time visual problems, its data comes extremely fast without any intensity information as the usual image. Each event also only carries very little information (only a single pixel coordinate and its polarity are transmitted at each timestamp). Therefore, it is not trivial to apply the standard computer vision techniques to event data. Recently, the event camera is gradually becoming more popular in the computer vision and robotics community. Many problems such as camera calibration and visualization [3], 3D reconstruction [4], simultaneous localization and mapping (SLAM) [5], pose tracking [6], have been actively investigated.

Our goal in this work is to develop a method which estimates the 6 Degrees of Freedom (6DOF) pose of the event camera using deep learning approach. The problem of effectively and accurately interpreting the pose of the camera plays an important role in many robotic applications such as navigation and manipulation. However, in practice it is challenging to estimate the pose of the event camera since it can capture a lot of events in a short time interval, while each event does not have enough information to perform the estimation. We propose to form a list of events into an event image and regress the camera pose from this image with a deep neural network. The proposed approach can accurately regress the camera pose directly from the input events, no additional information such as the 3D map of the scene or the continuous camera trajectory is needed.

In computer vision, Kendall et al. [7] introduced a first deep learning framework to regress the 6DOF camera pose from a single image. The authors showed that by using convolution neural networks (CNN) to learn deep features, the result is more robust to difficult lighting condition or motion blur in comparison with traditional keypoint approaches. Recently, the work in [8] introduced a method that used geometry loss function to learn the spatial dependencies. In this study, we follow the same concept that uses CNN to learn deep features, however unlike [8] that built a geometry loss function based on the 3D points of the scene, we use a SP-LSTM network to encode the geometry information. Our approach is fairly simple but shows significant improvement over the state-of-the-art methods.

The rest of the paper is organized as follows. We review the related work in Section II follow by the description of the event data and event images in Section III. We present the deep neural network architecture in Section IV and our experimental results in Section V. Finally, we conclude the paper and discuss the future work in Section VI.

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II. RELATED WORK

The event camera is particularly suitable for real-time motion analysis or high-speed robotics applications since it has low latency [3]. Early work on event camera used this property to track an object in order to provide fast visual feedback for controlling a simple robotic system [9]. The authors in [6] set up an onboard perception system with an event camera for 6DOF pose tracking of a quadrotor. Using the event camera, the quadrotor’s poses can be estimated with respect to a known pattern during high-speed maneuvers. Recently, a 3D SLAM system was introduced in [5] by fusing frame-based RGB-D sensor data with event data to produce a sparse stream of 3D points. This sparse stream is a compact representation of the input events, hence uses less computational resource and enables fast tracking.

In [10], the authors presented a method to estimate the rotational motion of the event camera using two probabilistic filters. Recently, Kim et al. [4] extended this system with three filters that simultaneously estimate the 6DOF pose of the event camera, the depth and the brightness of the scene. The work in [11] introduced a method to directly estimate the angular velocity of the event camera based on a contrast maximization design without requiring optical flow or image intensity estimation. In [12], the authors proposed to fuse visual data from a moving event camera with inertial data from an IMU to perform trajectory estimation. More recently, Reinbacher et al. [13] introduced a method to track an event camera based on a panoramic setting that only relies on the geometric properties of the event stream.

In computer vision, 6DOF camera pose estimation is a well-known problem. Recent research trend investigates the capability of deep learning for this problem [7] [8] [14]. Kendall et al. [7] introduced a first deep learning framework to regress the 6DOF camera pose from a single input image. The work of [15] used Bayesian uncertainty to correct the camera pose. Recently, the authors in [8] introduced a geometry loss function based on 3D points of the scene to let the network encode the geometry information during the training phase. Walch et al. [14] used a CNN and four parallel LSTM together to learn the spatial relationship in the image features space. The main advantage of the deep learning approach over the keypoint approach is the deep features are more robust to motion blur or difficult lighting condition in the input images.

This paper follows the recent trend in computer vision by using a deep network to estimate the pose of the event camera. We first create an event image from a list of events. A deep network comprises a CNN and a SP-LSTM is then trained end-to-end to regress the 6DOF camera pose. Unlike [8] that used only CNN with a geometry loss function that required the 3D points of the scene, or [14] that used four parallel LSTM to encode the geometry information, we propose to use Stacked Spatial LSTM to learn spatial dependencies from event images. To the best of our knowledge, this is the first deep learning approach that can successfully estimate the pose of the event camera.

A. Event Camera

Instead of capturing an entire image at a fixed time interval as the standard frame-based cameras, the event cameras only capture a single event at a timestamp based on the brightness changes at a local pixel. In particular, an event $e$ is a tuple $e = (e_t, (e_x, e_y), e_p)$ with $e_t$ is the timestamp of the event, $(e_x, e_y)$ is the pixel coordinate and $e_p = \pm 1$ is the polarity that denotes the brightness change at the current pixel. The events are transmitted asynchronously with their timestamps using a sophisticated digital circuitry. Recent event camera such as DAVIS 240C [1] comes with synchronized IMU and global-shutter grayscale images. In this work, we only use the event stream as the input for our deep network.

B. From Events to Event Images

Since a single event only contains a binary polarity value of a pixel, it does not carry enough information to estimate the 6DOF pose of the camera. In order to make the pose estimation problem using only the event data becomes feasible, similar to [11] we assume that $n$ events in a very short time interval will have the same camera pose. This assumption based on the fact that the event camera can capture a lot of events during a short duration, while in a very short time interval, the poses of the camera can be considered as not changing significantly. From a list of $n$ events, we reconstruct an event image $I \in \mathbb{R}^{h \times w}$ (with $h$ and $w$ are the height and width resolution of the event camera) based on the value of the polarity $e_p$ as follow:

$$I(e_x, e_y) = \begin{cases} 
0, & \text{if } e_p = -1 \\
1, & \text{if } e_p = 1 \\
0.5, & \text{otherwise}
\end{cases}$$ (1)

This conversation allows us to transform a list of events to an image and apply traditional computer vision techniques on event data. Since the event camera mainly captures the events at the edge of the scene, the event images are clearer...
on simple scenes, while more disorder on cluttered scenes. Fig. 2 shows some examples of event images. In practice, the parameter $n$ plays an important role since it affects the quality of the event images, which are used to train and infer the camera pose. We analyze the effect of this parameter to the pose estimation results in Section IV.D.

IV. POSE ESTIMATION FOR EVENT CAMERA

A. Problem Formulation

Inspired by [7] [15], we solve the 6DOF pose estimation task as a regression problem using a deep neural network. Our network is trained to regress a pose vector $y = [p, q]$ with $p$ represents the camera position and $q$ represents the orientation in 3D space. We choose quaternion to represent the orientation since we can easily normalize its four dimensional values to unit length to become valid quaternion. The groundtruth pose labels are obtained through an external mechanism to encode the knowledge of previous inputs at the parameter $n$ on simple scenes, while more disorder on cluttered scenes. In practice, the parameter $n$ plays an important role since it affects the quality of the event images, which are used to train and infer the camera pose. We analyze the effect of this parameter to the pose estimation results in Section IV.D.

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C. Pose Estimation with Stacked Spacial LSTM

Our pose regression network is composed of two components: a deep CNN and a SP-LSTM network. The CNN network is used to learn deep features from the input event images. After the last layer of the CNN network, we add a dropout layer to avoid overfitting. The output of this CNN network is reshaped and fed to the SP-LSTM module. A fully connected layer is then used to discard the relationships in the output of LSTM. Here, we note that we only want to learn the spatial dependencies in the image features through the input of LSTM, while the relationships in the output of LSTM should be discarded since the components in the pose vector are independent. Finally, a linear regression layer is appended at the end to regress the seven dimensional pose vector. Fig. 3 shows an overview of our approach.

In practice, we choose the VGG16 [18] network as our CNN. We first discard its last softmax layer and add a dropout layer with the rate of 0.5 to avoid overfitting. The event image features are stored in the last fully connected layer in a 4096 dimensional vector. We reshape this vector to 64 × 64 in order to feed to the LSTM module with 256 hidden units. Here, we can consider that the inputs of LSTM are from 64 “feature” sentences, each sentence has 64 words, and the spatial dependencies are learned from these sentences. We then add another LSTM network to create an SP-LSTM with 2 layers. The output of LSTM module is fed to a fully connected layer with 512 neurons, following by another fully connected layer with 7 neurons to regress the pose vector. We choose the SP-LSTM network with 2 layers since it is a good balance between accuracy and training time.
D. Training

To train the network, we use the following objective loss function:

\[ L(I) = \| \hat{p} - p \|_2 + \| \hat{q} - q \|_2 \]  

(3)

where \( \hat{p} \) and \( \hat{q} \) are the predicted position and orientation from the network. In [8], the authors proposed to use a geometry loss function to encode the spatial dependencies from the input. However, this approach required a careful initialization and needed a list of 3D points to measure the projection error of the estimated pose, which is not available in the groundtruth of the dataset we use in our experiment.

For simplicity, we choose to normalize the quaternion to unit length during testing phrase, and use Euclidean distance to measure the difference between two quaternions as in [7]. Although in theory, this distance should be measured in spherical space, in practice the deep network outputs the predicted quaternion \( \hat{q} \) close enough to the groundtruth quaternion \( q \). This makes the difference between the spherical and Euclidean distance becomes insignificant. We train the network for 1400 epochs using stochastic gradient descent with 0.9 momentum and 1e-6 weight decay. The learning rate is empirically set to 1e-5 and kept unchanged during the training. It takes approximately 2 days to train the network from scratch on a Tesla P100 GPU.

V. EXPERIMENTS

A. Dataset

We use the event camera dataset that was recently introduced in [3] for our experiment. This dataset included a collection of scenes captured by a DAVIS camera in a variety of synthetic and real environments. In addition to the asynchronous event data, this dataset also provides the global-shutter intensity images and inertial measurements. The indoor scenes of this dataset have the groundtruth camera poses from a motion-capture system with sub-millimeter precision at 200 Hz, while the outdoor scenes do not have the groundtruth poses. In this work, we use 6 sequences (shapes_rotation, box_translation, shapes_translation, dynamic_6dof, hdr_poster, poster_translation) from the indoor scenes that have the groundtruth poses. These sequences are selected to cover different camera motions and scene properties.

In order to create event images, we use the timestamp of the motion-capture system to group events to an image. All the events with the timestamp between \( t \) and \( t+1 \) of the motion-capture system will be considered as having the same camera pose. This assumption technically limits the speed of the event camera to the speed of the motion-capture system (i.e. 200 Hz), however it allows us to use the groundtruth poses with sub-millimeter precision from the motion-capture system. For each sequence, we randomly select 70% of the data for training and the rest 30% for testing.

B. Baseline

We compare our experimental results with the following state-of-the-art methods: PoseNet [7] and Bayesian PoseNet [15]. Both PoseNet and Bayesian PoseNet use the GoogleNet [19] as the main CNN backbone to regress the camera pose. We generally follow the training process described in the associated papers and use the source code provided by the authors for a fair comparison. We note that all these methods use only the event images as the input and no further information such as 3D map of the environment or inertial measurements is needed.

For each sequence, we report the median and average error of the estimated poses in position and orientation separately. The predicted position is compared with the groundtruth using the Euclidean distance, while the predicted orientation is normalized to unit length before comparing with the groundtruth. The median and average error are measured in \( \text{mm} \) and \( \text{deg} \) for the position and orientation, respectively.

C. Pose Estimation Results

Table I summarizes the median and average error on 6 sequences from the event camera dataset [3]. From this table, we notice that the pose estimation results are significantly improved using our SP-LSTM network in comparison with the baselines that used only CNN [7] [15]. Our SP-LSTM achieves the lowest mean and average error in all sequences. In particular, SP-LSTM achieves 0.231m, 7.455° and 0.241m, 7.593°, respectively. Overall, this improvement is around 6 times in position error and 3 times in orientation error. This demonstrates that the spatial dependencies play an important role in the camera pose estimation process and our SP-LSTM network from scratch on a Tesla P100 GPU. 

![Table I: Pose Estimation Results](image)

| Sequence                  | PoseNet [7] | Bayesian PoseNet [15] | SP-LSTM (ours) |
|---------------------------|-------------|-----------------------|----------------|
|                           | Median Error | Average Error         | Median Error   |
| shapes_rotation           | 0.109m, 7.388° | 0.137m, 8.812°        | 0.142m, 9.557° |
| box_translation           | 0.193m, 6.977° | 0.212m, 8.184°        | 0.190m, 6.636° |
| shapes_translation        | 0.238m, 6.001° | 0.252m, 7.519°        | 0.264m, 7.235° |
| dynamic_6dof              | 0.297m, 9.332° | 0.298m, 11.242°       | 0.296m, 8.963° |
| hdr_poster                | 0.282m, 8.513° | 0.296m, 10.919°       | 0.290m, 8.710° |
| poster_translation        | 0.266m, 6.516° | 0.282m, 8.066°        | 0.264m, 5.459° |
| **Average**               | 0.231m, 7.455° | 0.246m, 9.124°        | 0.241m, 7.593° |

**TABLE I**

**Pose Estimation Results**
successfully learns these dependencies, hence significantly improves the results. We also notice that PoseNet performs slightly better than Bayesian PoseNet, and the uncertainty estimation in Bayesian PoseNet can not improve the pose estimation results for event data.

From Table I we notice that the pose estimation results also depend on the properties of the scene in each sequence. Due to the design mechanism of the event-based camera, the events are mainly captured around the contours of the scene. In cluttered scenes, these contours are ambiguous due to non-meaningful texture edge information. Therefore, the event images created from events in these scenes are very noisy. As the results, we have observed that for sequences in cluttered or dense scenes (e.g. hdr_poster), the pose estimation error is higher than sequences from the clear scenes (e.g. shapes_rotation, shapes_translation). We also notice that dynamic objects (e.g. as in dynamic_6dof scene) also affect the pose estimation results. While PoseNet and Bayesian PoseNet are unable to handle the dynamic objects and have high position and orientation errors, our SP-LSTM gives reasonable results in this sequence. It demonstrates that by learning the spatial dependencies with SP-LSTM, the network can automatically discard the dynamic objects that can affect the pose estimation results.

Error Distribution Fig. 4 shows the position and orientation error distributions of our SP-LSTM network. Each box plot represents the error for one sequence. We recall that the top and bottom of a box are the first and third quartiles that indicate the interquartile range (IQR), the band inside the box is the median. We notice that the IQR of position error of all sequences (except the hdr_poster) is around 0.02m to 0.05m, while the maximum error is around 0.09m. The IQR of orientation error is in the range 1.5° to 3.5°, and the maximum orientation error is only 6°. In all 6 sequences in our experiment, the hdr_poster gives the worst results. This is explainable since this scene is a dense scene, hence the event images have uncleared structure and very noisy. Therefore, it is more difficult for the network to learn and predict the camera pose from these images.

Reproducibility We implement the proposed method using Tensorflow framework [20]. The testing time for each new event image using our implementation is around 5ms on a Tesla P100 GPU, which is comparable to the real-time performance of PoseNet, while the Bayesian PoseNet takes longer time (approximately 240ms) due to the uncertainty analysis process. To encourage further research, we will release our source code and trained models that allow reproducing the results in this paper.
D. Robustness to Number of Events

In this work, we assume that $n$ events occurring between two timestamps of the external camera system will have the same camera pose. Although this assumption is necessary to use the groundtruth poses to train the network, it limits the speed of the event-based camera to the sampling rate of the external camera system. To analyze the effect of number of events to the pose estimation results, we perform the following study: During the testing phase, instead of using all 100% of events from two continuous timestamps, we gradually use only 10%, 20%, ..., 90% of these events to create the event images (the events are chosen in order from the current timestamp to the previous timestamp). Fig. 3 shows the position and orientation errors of our SP-LSTM network in this experiment. From the figure, we notice that both the position and orientation errors of all sequences become consistent when we use around 60% number of events. When we use more events to create the event images, the errors are slightly dropped but not significantly. This suggests that the SP-LSTM network still performs well when we use less events. We also notice that using our current method to create the event images, some of the events may be overwritten when they occur at the same coordinates but have different polarity values with the previous events.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we introduce a new method to estimate the 6DOF pose of the event camera with a deep network. We first create the event images from the event stream. A deep convolutional neuron network is then used to learn features from the event image. These features are reshaped and fed to a Stack Spatial LSTM network. We have demonstrated that by using the Stack Spatial LSTM network to learn spatial dependencies in the feature space, the pose estimation results can be significantly improved. Moreover, our experimental results show that our method can perform well given a smaller number of events. This suggests that the network is currently limited by the sampling rate of the external groundtruth camera system.

Currently, we employ a fairly simple method to create the event image from a list of events. Our forming method works directly on event stream and does not check if the event at the local pixel has occurred or not. Since the input of the deep network is the event images, better forming method can improve the pose estimation results, especially on the cluttered scenes since the data from event cameras are very disorder. Another interesting problem to study is the compact network architecture that can achieve competitive pose estimation results while having fewer layers and parameters. This would improve the speed of the network and allow it to be used in more realistic scenarios.

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