EDDD: Event-Based Drowsiness Driving Detection Through Facial Motion Analysis With Neuromorphic Vision Sensor

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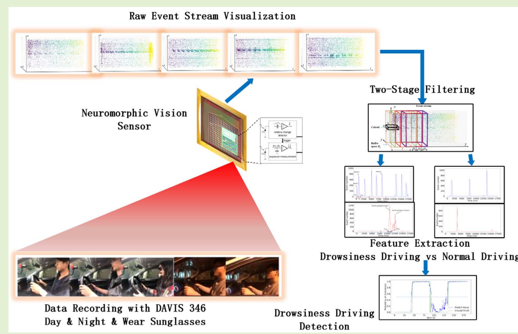

***Abstract*—Drowsiness driving is a principal factor of many fatal traffic accidents. This paper presents the first event-based drowsiness driving detection (EDDD) system by using the recently developed neuromorphic vision sensor. Compared with traditional frame-based cameras, neuromorphic vision sensors, such as Dynamic Vision Sensors (DVS), have a high dynamic range and do not acquire full images at a fixed frame rate but rather have independent pixels that output intensity changes (called events) asynchronously at the time they occur. Since events are generated by moving edges in the scene, DVS is considered as an efficient and effective detector for the drowsiness driving-related motions. Based on this unique output, this work first proposes a highly efficient method to recognize and localize the driver's eyes and mouth motions from event streams. We further design and extract event-based drowsiness-related features directly from the event streams caused by eyes and mouths motions, then the EDDD model is established based on these features. Additionally, we provide the EDDD dataset, the first public dataset dedicated to event-based drowsiness driving detection. The EDDD dataset has 260 recordings in daytime and evening with several challenging scenes such as subjects wearing glasses/sunglasses. Experiments are conducted based on this dataset and demonstrate the high efficiency and accuracy of our method under different illumination conditions. As the first investigation of the usage of DVS in drowsiness driving detection applications, we hope that this work will inspire more event-based drowsiness driving detection research.**

***Index Terms*— Event-based camera, neuromorphic vision, drowsiness driving detection.**

I. Introduction

DRIVING for an extended period is prone to trigger drowsiness of drivers, which is a serious threat to road safety. There is substantial statistical evidence to indicate that drowsiness driving is one of the primary reasons for many traffic accidents, casualties, and property losses all over the world. The National Highway Traffic Safety Administrator (NHTSA) reported that there are about 100,000 crashes in the USA caused by drowsiness driving annually, which results in more than 1500 death and 71,000 injuries [1].

Therefore, a lot of research efforts have been made on addressing the hazards of road safety caused by drowsiness driving [2], [3]. Drowsiness is characterized by the imbalance of physiological and psychological functions of drivers, leading to abnormal driving behaviors and unusual motion characteristics of the vehicle [4]. In the early stages of drowsiness driving detection research, many works are carried out based on the analysis of abnormal changes of driver's bio-signals [5]. Studies have found that drowsiness results in slow response and unusual operations of divers, driving behaviours such as brake, acceleration and steering are proved to be valid indicators for drowsiness driving detection [6]. There are also many research works to detect drowsiness driving based on the physical features of drivers,

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it's found that driver's facial expressions as well as eyes and mouth movements are significant signals implying drowsiness state [7]. Among various sensors, cameras are widely used in drowsiness driving detection due to properties of low cost and non-invasive. Meanwhile, the recent development of machine learning algorithms such as deep convolutional neural networks [8], [9] and stacked autoencoder [10] advance the research of the drowsiness detection model. Although current vision-based methods show great performance [11] in drowsiness driving detection, most of them are significantly depend on illumination conditions, and cannot fundamentally solve this problem due to the physical limitation of sensors. A typical example is when drivers' face are partial occlusion (glass, sunglasses and facial hair), traditional frame-based cameras can not sense the state of the driver's eyes, which may result in a failure of drowsiness driving detection [12].

In this paper, a novel drowsiness driving detection method by using neuromorphic vision sensors is presented. Comparing to traditional frame-based cameras, the neuromorphic vision sensor [13] is a new passive sensing modality that captures motions in the scene as an asynchronous sequence of events with high temporal resolution instead of sampling visual information with a fixed frame rate [14]. As it has the ability to capture motions such as eye blinking and yawning with ultra-high speed, which inspires us to develop a high efficient method to recognize and localize drivers' eyes and mouths directly from event streams. We further design and extract event-based drowsiness-related features from these motions to build an event-based drowsiness driving detection model. The contribution of this work includes three aspects:

- Firstly, the proposed method fully exploits the inherent advantage of neuromorphic vision sensors that only capture the motion in the scene as an asynchronous sequence of events with high temporal resolution. Driver's facial motions such as eyes blinking and mouth opening-closing are naturally detected by neurmorphic vision sensors, which enable less workload and computing resources for data processing.
- Secondly, a novel method is proposed for recognizing eyes and mouth motion from event streams and extracting dynamic drowsiness-related features from event streams caused by eyes and mouth motions with microsecond precision.
- Thirdly, to facilitate more interests and efforts to participate in the research community of drowsiness driving detection, this paper provides the first *event-based drowsiness driving detection dataset* (EDDD dataset) collected by a neuromorphic vision sensor.

The rest of this paper is organized as follows: neuromorphic vision sensors and some existed measures proposed for drowsiness driving detection are introduced in Section II. In Section III, the first neuromorphic vision sensor based dataset for drowsiness driving detection is designed. In Section IV, the process of establishing the EDDD method is described in detail. In section V, with the EDDD dataset, a set of experiments is conducted to validate the performance of the proposed method. Finally, this work was concluded in Section VI.

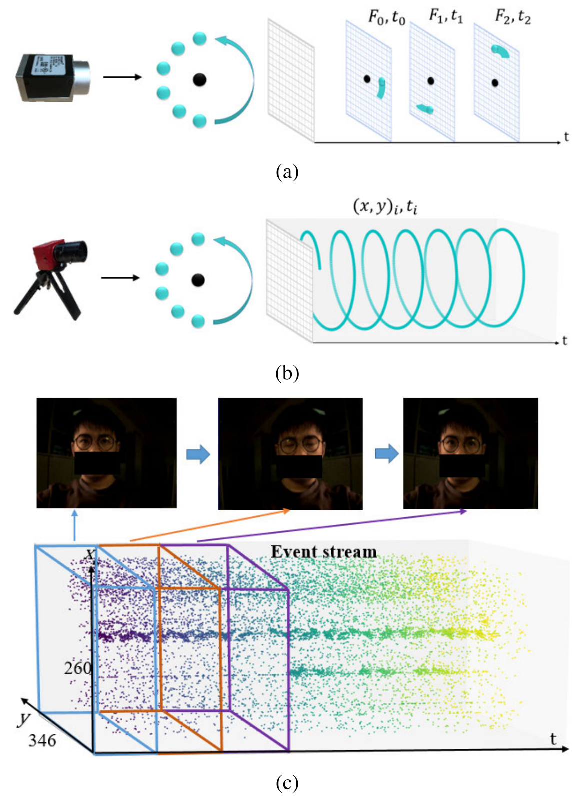


Fig. 1. (a) The frame-based camera captures all pixel intensities at a fixed frame rate. (b) The neuromorphic vision sensor captures intensity changes caused by the moving objects asynchronously. (c) Event stream from a neuromorphic vision sensor when recording a subject' face. The top-left three sub-figures correspond to three event stream slices, for the visualization comparison purpose.

II. Related Works

A. Neuromorphic Vision Sensor

The neuromorphic vision sensor is a new type of alternative vision sensor signal acquisition based paradigm [15]. Inspired by human visual system, it achieves redundancy suppression and low latency via precise temporal and asynchronous level crossing sampling as opposed to the classical spatially dense sampling at fixed frequency implemented in traditional frame-based cameras. The differences between neuromorphic vision sensors and traditional frame-based cameras are shown in Fig. 1. The black ball is static while the blue ball makes a fast circular motion around the black ball, the traditional frame-based camera and the neuromorphic vision sensor are used to observe two balls simultaneously. The traditional frame-based camera captures all pixel intensities at a fixed frame rate, the blue ball appears as a blurred trajectory on the image due to the fast motion speed, as Fig. 1(a) shows. The neuromorphic vision sensor only captures the motion caused by the fast-moving blue ball with high temporal resolution while information of stationary objects (black ball and background) are not caught as the Fig. 1(b) shows.

The output of neuromorphic vision sensors is called events and they transmitted asynchronously and timestamped with microsecond precision. Due to the unique output of neuromorphic vision sensors, traditional computer vision algorithms cannot be readily applied because no static scene information is encoded. Currently, there are two main approaches proposed for processing the output of neuromorphic vision sensors: *Convert event streams to image frame* and *Process event streams directly* [16]. There are two approaches to convert event streams into the image frame: fully frame-based conversion and semi frame-based conversion. The fully frame-based conversion is accumulating events with a fixed time slices or a fixed number of events [17]. The semi frame-based conversion processes the event streams before converting them into frame-based images, such as LIF (leaky integrate-and-fire) [18]. Processing the output of the neuromorphic vision sensor directly can achieve real-time information acquisition and utilization, which is an excellent fit to researches of road safety. Recently, more and more research interests are focused on processing event streams directly and there are several approaches proposed to utilize the spatio temporal information of event streams, such as 6-DOF algorithm for pose tracking [19] and PointNet for gesture recognition [20]. It is also found that neuromorphic vision sensors can get great performance on face detection [21].

B. Drowsiness Driving Detection

Drowsiness can be defined as a physiological change process that accumulates over time as human bodies translate from awake state to drowsy state [22]. It has been a prominent research topic in the domains of intelligent transport system (ITS) and intelligent vehicle (IV). To reduce traffic accidents caused by drowsiness driving, there are many researchers, institutes, and automotive corporations contributing their efforts on drowsiness driving detection, and bring about fruitful achievements, these can be divided into three categories: biological signal-based drowsiness driving detection, vehicle-based drowsiness driving detection, and behavior-based drowsiness driving detection.

The biological signal-based methods can get high accuracy in drowsiness driving detection, but the process of signal acquisition is invasive to the human body, which is troublesome for end users. Vehicle-based methods are non-invasive. However, the performance of such methods can be deteriorated by some interference, such as car vibration, road condition, and the driving skills of the driver, which are still not practically acceptable. Behavior-based methods use vision sensors to observe behaviors of drivers in a non-invasive way, which aroused the interests of many researchers. Most of the existed behavior-based drowsiness driving detection methods are proposed based on the state of head, mouth, and eyes. Head pose is proved to be a good indicator of drowsiness, Tawari *et al.* [23] used a 3D model to estimate the head pose by tracking facial features and analyze its geometric configuration. Martin *et al.* [24] present multi-perspective framework based on a shape feature to monitor the drivers head dynamics continuously. Kaplan *et al.* [25]

TABLE I
SYMBOLS USED IN THIS WORK

Symbol	Introduction of the symbols	Units
e	event collected by DAVIS 346	-
(x, y)	the horizontal/vertical coordinate value of the event in the pixel coordinate system.	-
t	the timestamp when events occur	us
U_{ti}	membrane potential	-
U_0	initial value of membrane potential	-
u	increase rate of the neuron's MP	-
α	threshold for filtering event noises in the cuboid	-
λ	decay rate of the neuron's MP	-
θ	the threshold of the MP	-
$\boldsymbol{e}$	set of events generated by the driver's eyes and mouth motions.	-
B_j	buffer space of sliding buffer space mechanism	-
$\mathbf{M}$	count matrix	-
Δt	updating rate of sliding buffer space mechanism	ms
b_j	small grids	-
l_w	label for small grids	-
c	final number of event cluster	-
B_f	blink frequency	-
T_d	a fixed time duration	s
n	number of blinks in the fixed time duration	-
B_d	the average blink duration in a fixed time	s
b_d	duration of one blink action	s
t_{db}	the time of eyelids start to move downwards	ms
t_{ub}	the time when eyelids move back upwards	ms
M_f	mouth opening-closing frequency	-
m	number of mouth opening-closing in a fixed time duration	-
M_d	the average mouth opening-closing duration in a fixed time	-
m_d	the duration of one opening-closing	-
t_{um}	the time when the lips start to move upwards in a mouth open motion	-
t_{dm}	the time when the lips move back downwards in a mouth open motion	-
$\mathbf{x}$	drowsiness feature vector	-
T_w	time window in the sliding window detection mechanism	s
Δd	sliding step of the sliding window detection mechanism	ms
v_p	the predict value of drowsiness driving detection model	-
θ_d	the decision threshold of the EDDD method	-

summarized that nodding is a precise and effective indicator for drowsiness driving detection. Yawning caused by drowsiness or boredom is another visible clues to demonstrate drivers who might fall asleep. Anitha *et al.* [26] proposed a novel yawning detection system based on a two-agent expert system. Sikander and Anwar [11] proposed an approach to detect yawning by extracting geometric and appearance features of both mouth and eyes regions. In recent research, Knapik and Cyganek [27] proposed a drowsiness driving recognition methods based on yawn detection in thermal images, it can operate in day and night conditions without distracting a driver due to the usage of thermal images. In addition, eye state is also widely used to estimated drowsiness level of the driver. The most frequently used parameters PERCLOS [28] and EBR [29] (eye blink rate) can measure the drowsiness level of drivers with high accuracy, which are adopted as drowsiness estimation indicators on many occasions. Besides, increased blink frequency, a long duration for eye closure are also obvious signs of facial expressions that can reflect the drowsiness level of driver [30]. To improve the accuracy of drowsiness driving detection, multi-feature fusion is in the current research trend. Zhao *et al.* [31] employed learning-based classifiers Adaboost and multi-nomial ridge regression

TABLE II

DESCRIPTION OF THE EDDD DATASET. BFD: DRIVING WITH BARE FACE DURING THE DAY; GD: DRIVING WITH GLASSES DURING THE DAY; SGD: DRIVING WITH SUNGLASSES DURING THE DAY; BFN: DRIVING WITH THE BARE FACE AT NIGHT; GN: DRIVING WITH GLASSES AT NIGHT

Scenarios	Day/Night	Face occlusion	Number of video clips (per scenario)	Video clip duration (s)	Drivers' actions
BFD	Day	wearing glasses/sunglasses	52	18-24	speaking/blinking/yawning
GD	Day	wearing glasses	52	17-24	speaking/blinking/yawning
SGD	Day	wearing sunglasses	52	19-25	speaking/blinking/yawning
BFN	Night	None	52	18-25	speaking/blinking/yawning
GN	Night	wearing glasses	52	19-26	speaking/blinking/yawning

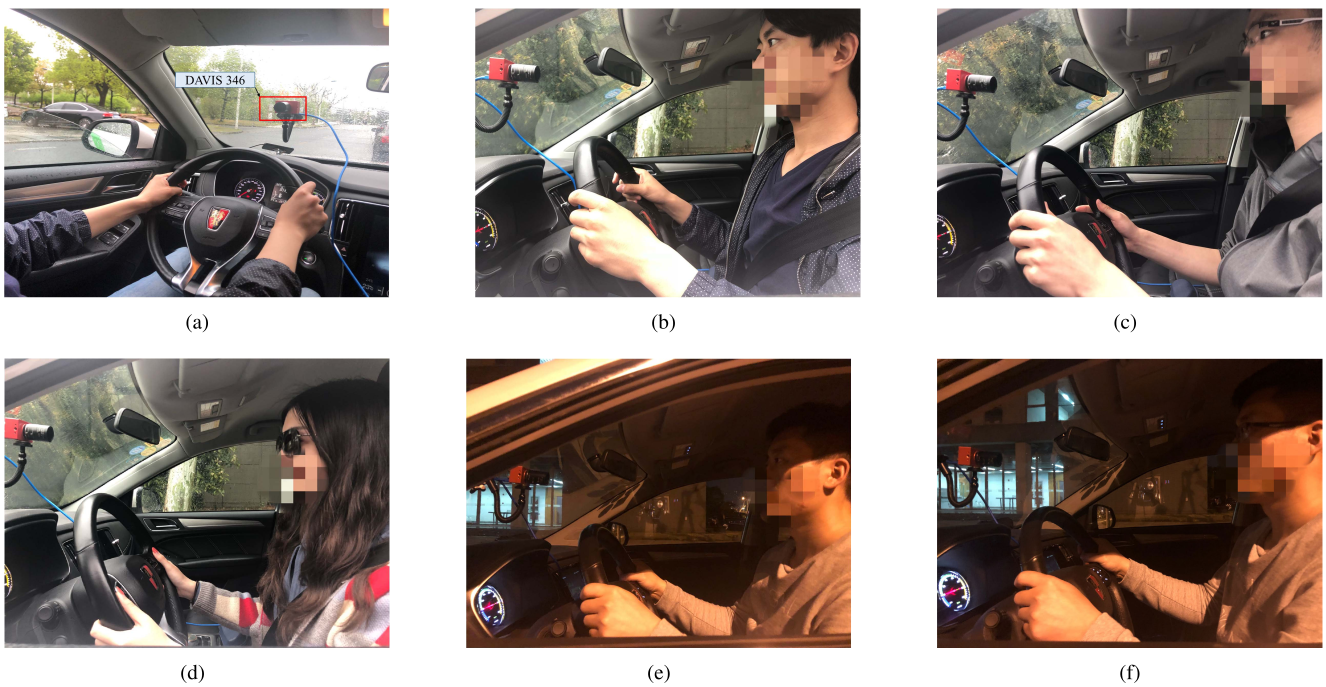


Fig. 2. Visualization of the recording environment with a RGB camera. (a) Installation location of DAVIS 346; (b) Scenario BFD; (c) Scenario GD; (d) Scenario SGD; (e) Scenario GN; (f) Scenario BFN.

to detect drowsiness based on the blink and yawn analysis. Mbouna *et al.* [32] propose a driver alertness monitoring system by using visual features such as eye index (EI), pupil activity (PA), and head pose (HP). Ji *et al.* [33] found that the visual cues employed characterize eyelid motion, gaze motion, head motion, and facial expressions can typically characterize the level of alertness of a person.

As vision-based drowsiness driving detection methods are non-invasive, this work continues with this direction. However, different with previous work, we investigate the first-ever usage of a neuromorphic vision sensor to research the driver drowsiness detection, which is motivated by it unique output data (event stream instead of RGB image) and high dynamic range (up to 180 dB).The symbols used in this paper are introduced in Table. I.

III. EDDD DATASET

There are several drowsiness driving detection datasets collected by traditional frame-based vision sensors [34], [35], which facilitates many researchers to carry out drowsiness driving detection research. However, no one has ever studied drowsiness driving detection based on neuromorphic vision sensors. Motivated by this, the first-ever event-based drowsiness detection dataset is provided by using a neuromorphic vision sensor named DAVIS 346. DAVIS 346 has a pixel resolution of 346×260 and a temporal resolution of 1 us. As shown in Fig. 2(a), the DAVIS 346 is mounted above the dashboard in vehicle and 0.5 meter away from the driver.

There are 26 volunteer drivers (3 females and 23 males) with more than three years of driving experience participated in the data collection. All participants should be in good health and have enough sleep. Besides, they were asked to refrain from consuming coffee or alcohol 24 hours before the data collection. Participates are required to drive in 5 different scenarios: Driving with bare face during the day (BFD), driving with glasses during the day (GD), driving with sunglasses during the day (SGD),driving with the bare face at night (BFN), driving with glasses at night (GN). In each scenario, subjects need to perform two different driving states:

- Normal driving: drivers are energetic and concentrate on driving tasks.

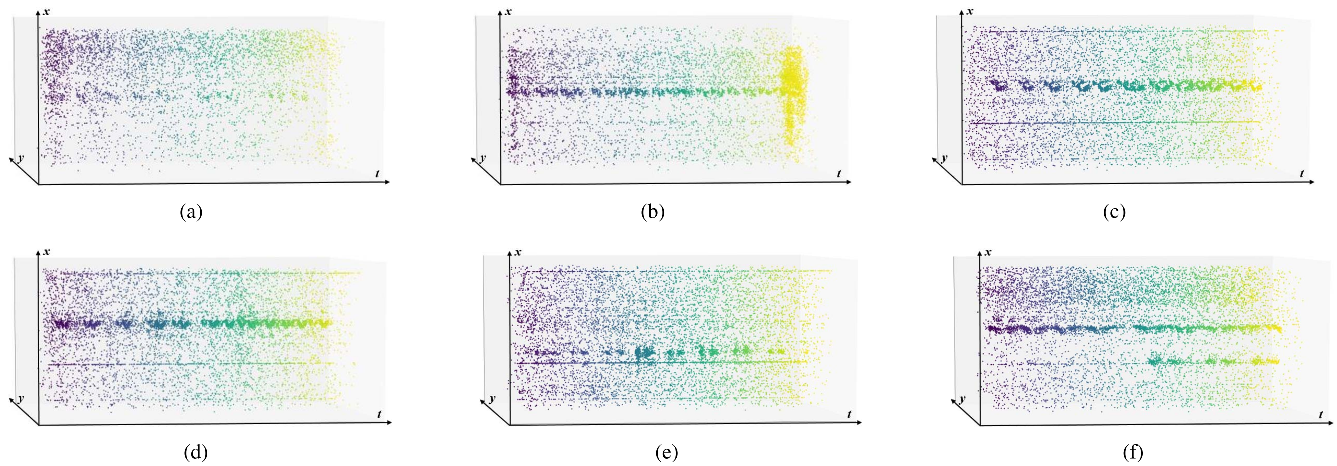


Fig. 3. Raw data visualization of the event slices from different recording scenarios. (a) No eyes blinking and mouth opening-closing. (b) Eyes blinking with bareface. (c) Eyes blinking with glasses. (d) Eyes blinking with sunglasses. (e) Mouth opening-closing only. (f) Eyes blinking and mouth opening-closing simultaneously.

- Drowsiness driving: drivers are drowsiness or fell sleepy and can't concentrate on driving tasks.

During the collection of the EDDD dataset, there are 10 video clips recorded for each subject and 52 video clips recorded for each scenario, each video clip lasts for about 20 seconds to show subjects' normal/drowsiness state. In total, there are 260 video clips in the EDDD dataset for 26 subjects recorded in 5 driving scenarios. Recording scenarios are shown in Fig. 2. Recording samples are shown in Fig. 3. Details of the EDDD dataset refer to Table. II.

IV. Methodology

In this section, an event-based drowsiness detection system based on EDDD dataset, named EDDD system, is proposed. The system framework is illustrated in Fig. 4. A two-stage filtering method is firstly proposed for pre-possessing the asynchronous event streams output from neuromorphic vision sensors. Then, driver's eyes and mouth motions are automatically recognized. With carefully designed drowsiness-related features, the EDDD system is trained with learning method to distinguish the drowsiness driving from normal driving.

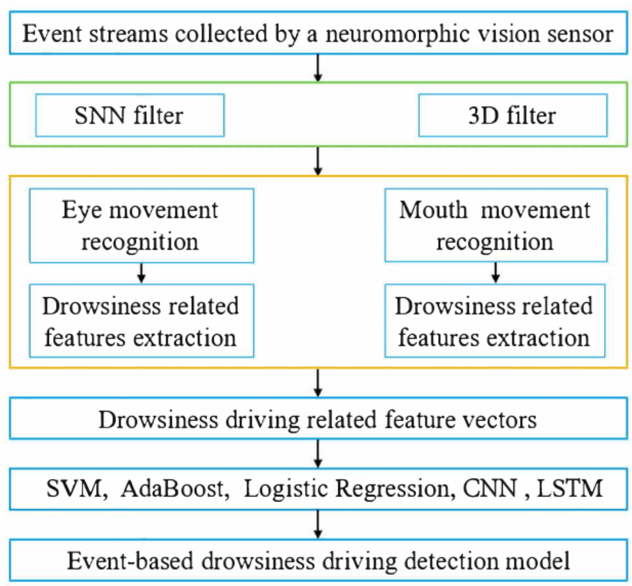


Fig. 4. Framework of the proposed EDDD method.

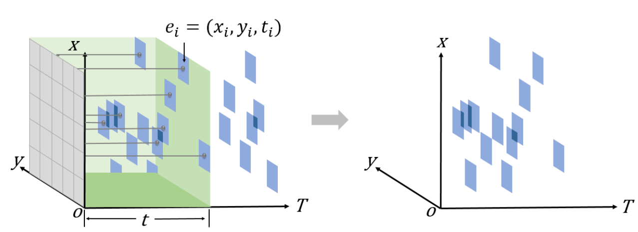


Fig. 5. Representing events as point cloud in 3D space.

A. Two-Stage Filtering

The main aim of this research study is to process the events which are highly related to the regions of eyes and mouth as the motions of the eyes and mouth are widely used for driver's drowsiness detection [31]–[33]. In the process of drowsiness driving, it is still inevitable that many events are triggered by the movements of facial muscles or from transistor circuit of the sensor which are called event noises in this work. Therefore, a two-stage filtering method is designed to remove these event noises to eliminate the potential interference in further processing stages such as eyes motion and drowsiness detection.

1) SNN Filter: Neuromorphic vision sensors such as DVS encodes temporal contrast of light intensity into streams of events which are then transmitted via asynchronous digital circuits, using the so-called address event representation (AER). Temporal contrast sensitivity is defined as the detection threshold across which a temporal contrast signal can elicit an event. A smaller threshold results in excessive output noise events, therefore making it difficult to obtain the events caused by eyes and mouth motions. Inspired by Spiking Neural Networks (SNNs), a SNN filter is designed to filter out low frequency signals such as the noise events mentioned above. The SNN filter models the brain's communication scheme that neurons use for information transformation via discrete

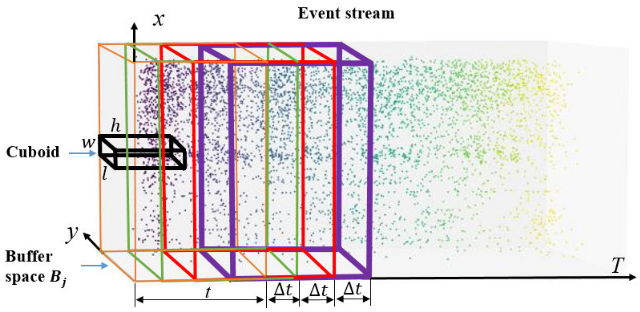


Fig. 6. The sliding buffer space mechanism for the 3D filter.

action potentials (spikes) in time through adaptive synapses. Events are donated as 4-tuple: $e = (x, y, t, p)$, where (x, y) represents the pixel coordinates of events in pixel coordinate system, t records the timestamp when events occur, and p is the polarity of events, which can be either ON ($p = 0$) or OFF ($p = 1$) [36]. In this research work, every image pixel (x_i, y_i) at timestamp t is regarded as a neuron with membrane potential (MP) of U_{ti}. The initial value of MP is U_0 ($U_0 = 0$), each incoming event at (x_i, y_i) will cause a increase of the neuron's MP with u regardless of its polarity, at the same time, MP decay at a fixed rate λ:

$$U_{ti} = U_0 + (1 - \lambda)(n - 1)u \tag{1}$$

where, n represents the number of events at (x_i, y_i). When the U_{ti} reaches a threshold θ in a specific time interval, e_j can be thought of being caused by the driver's eye or mouth motions:

$$\boldsymbol{e} = \left\{\left\{e_j, (j = 1, 2, \ldots\ldots, m)\right\} \middle| U_{tj} > \theta\right\} \tag{2}$$

where, θ is the threshold of the MP, which is determined empirically according to some experiments. Fig. 7(a) and Fig. 7(b) show two images (the raw event streams are converted to images by accumulated events in 10 ms for the visualization purpose) before and after the SNN filter. It can be seen that most of the randomly distributed noise events are filtered out. However, the noise events generated by the other motions such as the movements of glasses and eyebrow are relatively densely distributed, which can not be filtered by SNN filter.

2) 3D Filter: In a typical facial motion situation, such as eye blinking and yawning, events are almost entirely generated by the motion of eyelids, lips, as well as the facial muscles. It is observed that the motion of facial muscles is relatively small compared to the motions of the eyes and mouth such as eyes blinking. Therefore, a 3D filter is designed to filter out the noise events according to the event density of local spatial-temporal regions. Each event e_i is a point (x_i, y_i, t_i) in 3D space *O-XYT*, as shown in Fig. 5. Firstly, a cuboid is designed to traverse 3D space *O-XYT*, within which the number of events e_k is counted for checking spatio-temporal neighbourhood of each incoming event after SNN filtering. A threshold α is determined empirically to filter noise events in the cuboid according to Eq. 3:

$$\boldsymbol{e} = \{\{e_k, (k = 1, 2, \ldots\ldots, l)\} \,|U_{tk} > \theta \cap l > \alpha\} \tag{3}$$

Considering the high temporal resolution of neuromorphic vision sensor, it generates relatively few events at each timestamp ($1us$). So in the proposed research system, sliding buffer space mechanism is applied to store a predefined time duration $t = 10$ ms, as shown in Fig. 6, the events in buffer space B_j is updating with $\Delta t = 1$ ms, the latest 1 ms events are popped into the B_j each time while the earlier 1 ms events are flopped. For further filtering, the number of events in buffer space B_j for every updating is $s(s = l \times p)$, and these events are checked according to Eq.4.

$$\boldsymbol{E} = \{\{\boldsymbol{e}_z, (z = 1, 2, \ldots\ldots, p)\} \,|U_{tz} > \theta \cap s > \beta\} \tag{4}$$

where, β is a threshold determined empirically according to some experiments. The events processed by the 3D filter are also converted into an image frame for visualizing the effects of the 3D filter, as shown in Fig. 7(c).

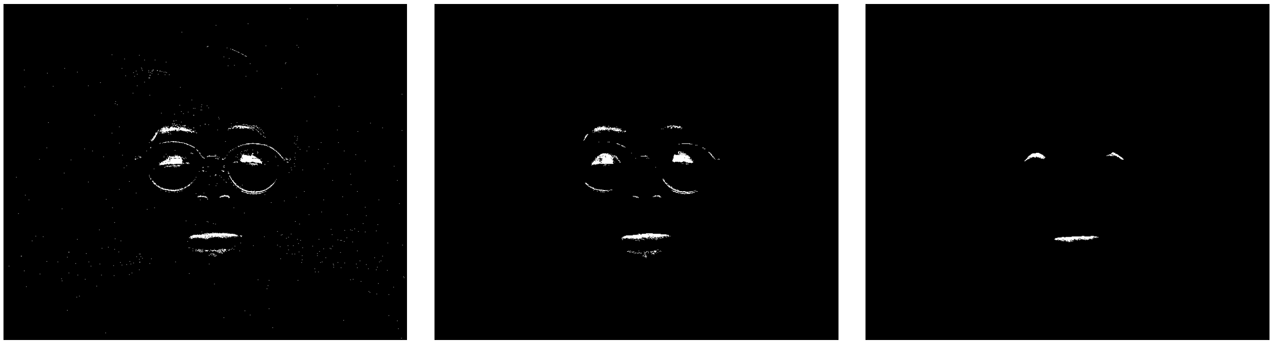
B. Eyes and Mouth Motion Recognition

The motions of eyes and mouth are important clues to distinguish the drowsiness driving from normal driving. There are four types of motions of eyes and mouth which occur randomly during the driving: eyes blinking, mouth open and close, simultaneous motions of eyes and mouth, no motions of eyes and mouth. Based on WaveCluster algorithm [37], events caused by eye blinking and mouth opening-closing can be accurately clustered. We use a sliding buffer space $B_j(j = 1, 2, \ldots, m)$ with size $346 \times 260 \times 10$ ms, and with updating step $\Delta t = 1$ ms to synchronize the frame-free event streams, and quantize the buff space B_j evenly into small grids $b_j(j = 1, 2, \ldots, n)$ of a specified size.

The number N of events in each grid b_j is counted and used to create a count matrix $\mathbf{M}$. Then, discrete wavelet transform is applied to the matrix $\mathbf{M}$ to find the connected components in the 6-neighborhood of the transformed count matrix $\mathbf{M}$, and assign label $l_w, (w = 1, 2, \ldots, n)$ to the grids based on which cluster that the events reside in, and make the look up table for mapping the clusters back to the pixel coordinates. Compare to the mouth opening-closing that only one event cluster is generated, eye blinks have a unique signature that two event clusters are generated simultaneously and they are distributed in parallel in space. Therefore, the final number $c, (c = 0, 1, 2)$ of cluster is obtained by merging events e_i with the same label. If c equals to 1, we determine whether is eye blinking or mouth opening-closing according to the position of the cluster. If c equals to 2, it means that eyes blinking and mouth opening-closing occur simultaneously. The main steps are shown in Algorithm 1.

C. Event-Based Drowsiness Driving Detection (EDDD) Model

Four drowsiness-related features are designed and extracted directly from event streams based on the eyes blinking detection and mouth opening-closing detection. Fig. 8 shows the number of events caused by eyes blinking and mouth opening-closing over time in typical normal and drowsiness driving scenarios. Each peak in Fig. 8 reflects one eyes blinking or mouth opening-closing action, which can be utilized to describe the



(a) (b) (c)

Fig. 7. Filtering results with two-stage filtering method. (a) Image converted by raw event streams; (b) Image converted by event streams processed by the SNN filter; (c) Image converted by event streams processed by the 3D filter.

Algorithm 1 Eyes and Mouth Motion Recognition

Input: The events $e_i (i = 1, 2, \ldots, n)$ after the two-stage filtering in a fixed time duration T.

Initialization: Define a sliding buff space $B_j (j = 1, 2, \ldots, m)$ with size $346 \times 260 \times 10(ms)$ and updating step $\Delta t = 1(ms)$.

Step1: Quantize the buff space B_j evenly into small grids $b_j (j = 1, 2, \ldots, n)$ of a specified size.

Step2: Count the number N of events in grid b_j, creating a count matrix $\mathbf{M}$.

Step3: Apply discrete wavelet transform to the matrix $\mathbf{M}$.

Step4: Find the connected components in the 6-neighborhood of the transformed count matrix $\mathbf{M}$.

Step5: Assign label $l_w, (w = 1, 2, \ldots, n)$ to the grids based on which cluster that the events reside in, and make the look up table for mapping the clusters back to the original multi-dimensional space.

Step6: Get the final number $c, (c = 0, 1, 2)$ of cluster by merging events e_i with the same label.

Step7:

if $c = 0$ **then**

  No eyes blinings or mouth opening-closing.

else

  if $c = 1$ **then**

    It is determined according to the position of the cluster that it is eye blinking or mouth opening-closing.

  else

    Eyes blinkings and mouth opening-closing occur simultaneously.

Output: Results of eyes and mouth motion recognition.

difference between normal driving and drowsiness driving. The proposed four drowsiness-related features were illustrated as follows:

• Blink frequency (B_f)

In a fixed time duration T_d, if there are n peaks in the curve of Fig. 8(a) and Fig. 8(c), it means that there are n blinks appeared in T_d, the blink frequency (B_f) can be expressed as:

$$B_r = \frac{n}{T_d} \tag{5}$$

• Blink duration (B_d)

In the proposed method, b_d indicates the duration of one blink action, it means an act of shutting and opening the eyes. The high temporal resolution of the neuromorphic vision sensor enables that the whole process of one blink is recorded. The eyelids start to move downwards is t_{db}, and the time when the eyelids move back upwards and fully open is t_{ub}. The duration b_d of one eye blink can be expressed as

$$b_d = t_{ub} - t_{db} \tag{6}$$

In a fixed time T_d, a driver blinks n times, the B_d can expressed as

$$B_d = \frac{\sum_i^n b_d}{n} \tag{7}$$

• Mouth opening-closing frequency (M_f)

In a fixed duration T, if there are m peaks in the curve of Fig. 8(b) and Fig. 8(d), these peaks are caused mouth opening-closing motions such as speaking and yawning, the mouth opening-closing frequency M_f can be expressed as

$$M_f = \frac{m}{T_d} \tag{8}$$

• Mouth opening-closing duration (M_d)

In the proposed system, mouth open duration M_d means the duration that mouth varies from open to close. We note that when the lips start to move upwards in a mouth open motion is t_{um}, and the time when the lips move back downwards is t_{dm}. The duration of one opening-closing can be expressed as

$$m_d = t_{dm} - t_{um} \tag{9}$$

In a fixed time T_d, a driver repeats the action of mouth opening-closing m times, the M_d can expressed as

$$M_d = \frac{\sum_i^m m_d}{m} \tag{10}$$

The four extracted drowsiness related features constitute the drowsiness feature vector $\mathbf{x}$

$$\mathbf{x} = [B_r, B_d, M_r, M_d] \tag{11}$$

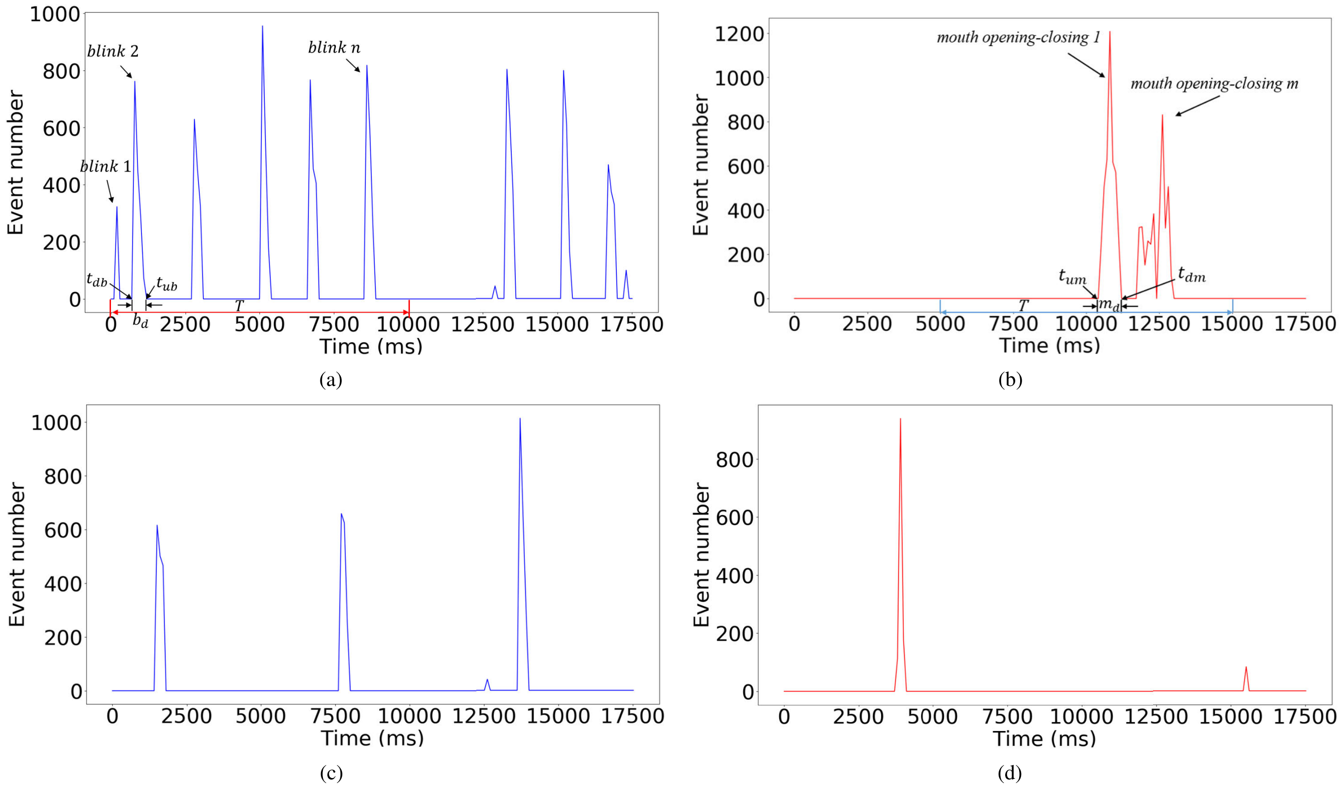


Fig. 8. Number of events generated by eyes blinking or mouth opening-closing over time in normal and drowsiness driving. (a) Events from eye blinking in a typical drowsiness driving scenario. (b) Events from mouth opening and closing in a typical drowsiness driving scenario. (c) Events from eye blinking in a normal driving scenario. (d) Events from mouth opening and closing in a normal driving scenario.

TABLE III
THE PERFORMANCE OF THE EDDD METHOD IN DIFFERENT DRIVING SCENARIOS

METHODS	BFD		GD		SGD		BFN		GN	
	AUC(%)	EER(%)	AUC(%)	EER(%)	AUC(%)	EER(%)	AUC(%)	EER(%)	AUC(%)	EER(%)
SVM + RBF	95.03	10.24	96.65	8.65	94.49	13.13	96.06	10.61	97.90	7.43
SVM + PKF	94.96	10.23	96.62	8.42	94.44	14.17	96.06	10.61	97.81	8.10
AdaBoost	95.30	10.21	96.70	9.44	95.06	11.02	96.33	9.52	98.21	5.41
LR	95.12	10.23	96.83	8.35	94.42	12.88	96.07	10.29	98.16	5.74
CNN	95.29	10.21	96.79	8.37	95.19	11.00	96.25	9.69	98.42	4.70
LSTM	99.78	0.58	99.65	0.86	99.82	0.38	99.77	0.47	99.99	0.14

Based on the four drowsiness-related features **x** and standard classifiers, an EDDD method for drow-siness driving detection is established. Drowsiness driving detection is formulated as a two-class classifier problem (normal driving and drowsiness driving) in this work. Four standard machine learning algorithms including SVM with a radial basis kernel function (SVM + BRF), SVM with a polynomial kernel function (SVM + PKF), AdaBoost, and logistic regression (LR) and two deep learning algorithms including CNN and LSTM are used.

V. EXPERIMENTS

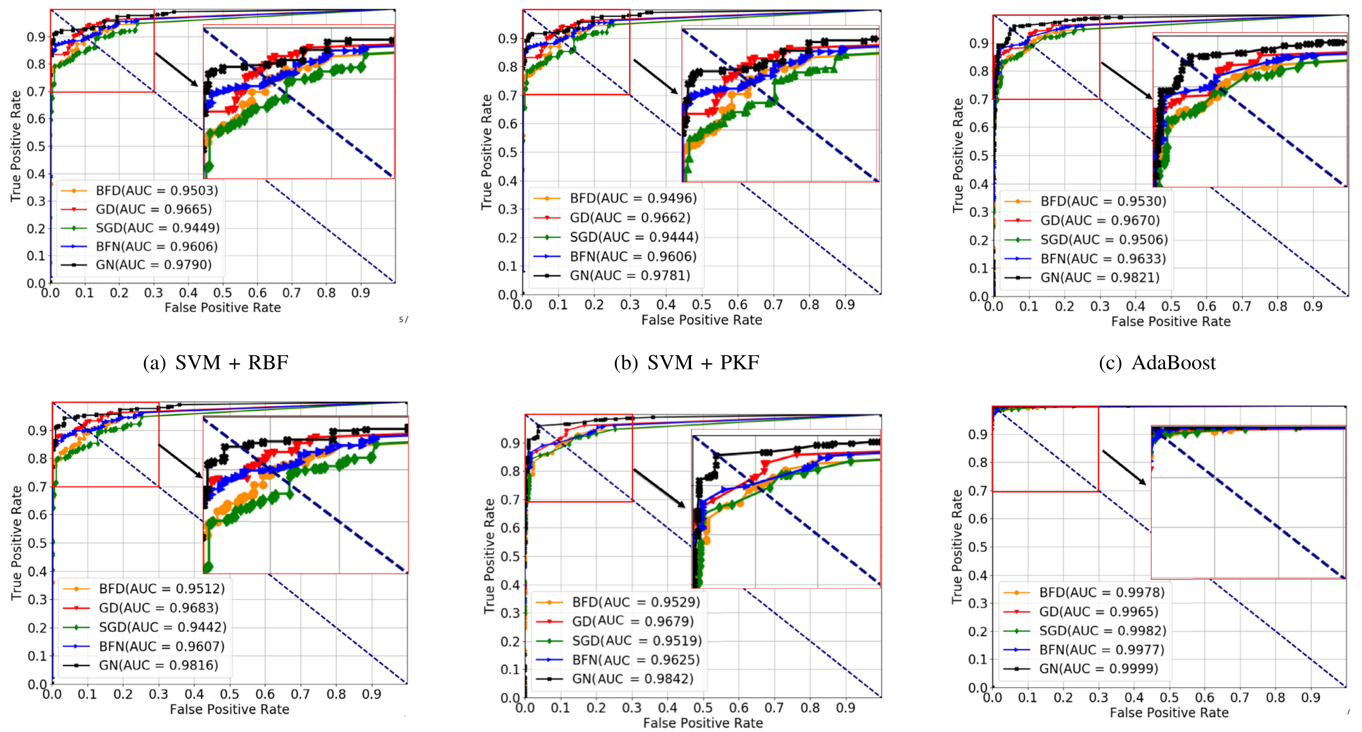
The experimental setup and results are presented in this section. The proposed EDDD system is evaluated on the EDDD dataset and the performance of the proposed method under different experimental conditions is analyzed in detail. An on-line drowsiness driving detection experiment is also performed.

A. Experimental Setup

The performance of the proposed method is evaluated in two phases. The EDDD dataset are divided into three parts: a training set (50%), a validation set (20%), and a testing set (30%). In the first phase, a set of experiments are conducted to evaluate the performance of the EDDD method under five different driving scenarios that are mentioned in Section III). In the second phase, several experiments are conducted to verify the online drowsiness driving detection performance of the EDDD method.

B. Experimental Results With EDDD Dataset

To evaluate the proposed EDDD model, some experiments are conducted based on the testing data collected in driving scenarios BFD, GD, SGD, BFN, and GN. Table. III shows the results of EDDD method with 4 standard classifiers and 2 deep learning algorithms in 5 different driving scenarios. Based



(a) SVM + RBF (b) SVM + PKF (c) AdaBoost

(d) LR (e) CNN (f) LSTM

Fig. 9. ROC curves of the EDDD method with the standard classifiers in five different driving scenarios. In order to observe the ROC curve more clearly, the upper left corner of each picture has been enlarged.

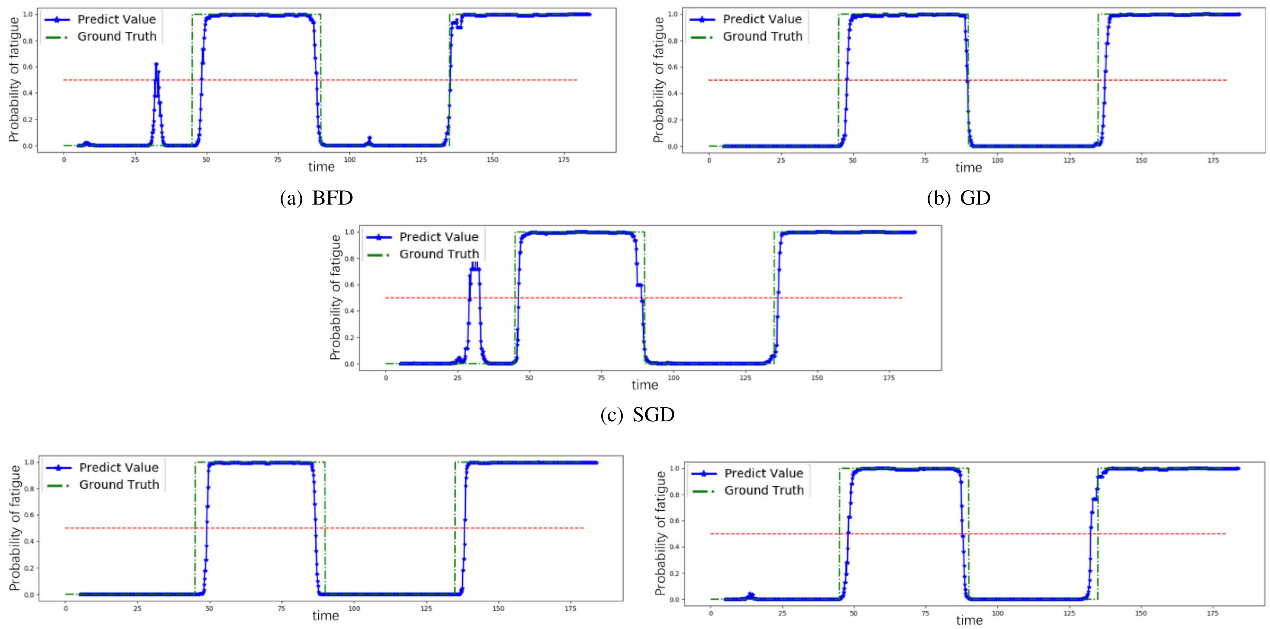
on average true positive rates (TPR) and false positive rates (FPR), and area under ROC curves (AUC) and the Equal Error Rate (EER) are used in the evaluations. In Fig. 9(a), the AUC is ranged from 94.49% to 97.90% and the EER is ranged from 7.43% to 13.13% with the classifier SVM + RBF; in Fig. 9(b), the AUC is ranged from 94.44% to 97.81% and the EER is ranged from 8.10% to 14.17% with the classifier SVM + PKF; in Fig. 9(c), the AUC is ranged from 95.06% to 98.21% and the EER is ranged from 5.41% to 11.02% with the classifier AdaBoost; in Fig. 9(d), the AUC is ranged from 94.41% to 98.16% and the EER is ranged from 5.74% to 12.88% with the classifier LR; in Fig. 9(e), the AUC is ranged from 95.29% to 98.42% and the EER is ranged from 4.70% to 11.00% with the deep learning algorithm CNN; in Fig. 9(f), the AUC is ranged from 99.65% to 99.99% and the EER is ranged from 0.14% to 0.86% with the deep learning algorithm LSTM. In the CNN-based EDDD system, the network has 4 layers (1 input layer, 2 convolutional layers, and 1 output layer) with a 1-D filter of 2*1. The input of the CNN is the drowsiness feature vector $\mathbf{x}$, and the output are the possibility of fatigue status. In the LSTM-based EDDD system, we use sequence features in 50s as input to LSTM, which is composed of a single layer with 64 LSTM cells, the output is transformed by the dense layer to the width of 2. In the end, a Softmax classifier is added to classify the fatigue status. We find that, in all scenarios, the LSTM-based EDDD method gets the best performance, which proves that the EDDD method we proposed can achieve good drowsiness driving detection performance even the driver is wearing glasses/sunglasses or driving at night.

C. On-Line Drowsiness Driving Detection

To achieve real-time drowsiness driving detection, a sliding window detection mechanism is designed with a time window of $T_w = 10$ s and a sliding step of $\Delta d = 200$ ms, as shown in Fig. 11. Drowsiness-related features are extracted directly from the event slice of $T_w = 10$ s window. Experiments are conducted to validate the on-line performance of drowsiness drowsiness driving detection in different scenarios (including BFD, GD, SGD, BFN, and GN). In each scenario, drivers are instructed to simulate the normal driving and drowsiness driving in a continuous way. The driver's normal driving state and drowsiness driving state are labeled as number 0 and 1, respectively. As show in Fig. 10, the green chain line represents the ground truth of driver's state, and the blue curve with triangle mark represents the predict value (υ_p) of the EDDD method with the classifier AdaBoost. The decision threshold θ_d of the EDDD methods is 0.5. If $\upsilon_p > \theta_d$, the driver is under drowsiness driving status, if $\upsilon_p < \theta_d$, the state of the driver is normal. From Fig. 10, we can see that in driving scenarios BFD, SGD, BFN, and GN, our EDDD model predict the drowsiness driving status precisely. In scenario BFD and GD, there is a false alarm in each of them which indicate that more complex features (e.g., new drowsiness-related features) and models (e.g., fusion model) are need to improve the robustness of the EDDD method.

D. Discussion

The proposed model is compared with state-of-the-art drowsiness driving detection methods in Table. IV. Although



(a) BFD (b) GD (c) SGD (d) BFN (e) GN

Fig. 10. Experimental results of online drowsiness driving detection with different scenarios. The green chain line lines represent the ground truth of driver's state, and the blue lines with triangle mark represent the probability of drowsiness predicted by EDDD method.

TABLE IV
COMPARISON OF THE EDDD METHOD WITH THE STATE-OF-THE-ART METHODS

Methods	Sensor	Drowsiness-related features	Advantages	Disadvantages	Accuracy(%)
[27]	camera	yawn	robust in day and night conditions	vulnerable to fast movements	90
[38]	electrodes	ECG signals	robust in real conditions	no real time performance	97.01
[39]	driving simulator	eleven steering wheel parameters	non-intrusive	no strong results	71.01
[6]	electrodes,driving simulator,camera,	physiological and behavioral indicators, driving behavior	robust in all conditions	invasive	97.8
[40]	driving simulator ,camera	steering features, facial features	low experiment cost, non-invasive	low accuracy	86.25
EDDD method	DAVIS 346	blinking frequency, blinking duration, mouth opening-closing frequency and duration	high accuracy, robust, low computational cost	can't move head intensely	94.42-99.99

the physiological signals related methods in [38] and [6] can get high accuracy for drowsiness driving detection, such methods often use wearable or invasive sensors to collect the physiological signals that are impractical in real driving scenario. While vehicle motion based fatigue driving detection methods [39] do not rely on any in-cockpit sensors, they are quite unstable because these methods are highly susceptible to the driving habits and road conditions. Additionally, vision-based drowsiness driving detection methods such as [27] and [40] are sensitive to illumination variations that are unstable in real driving environments. Instead, our preliminary investigation of the usage of the innovative neuromoprhic sensor addresses the above issues suffered by state-of-the-art approaches. In Table. III, we can see that our proposed method achieves stable drowsiness driving detection performances in different scenarios regardless of the illumination conditions and whether wearing sunglasses or not, which shows that our method enjoys a large intra-scene dynamic range. In addition, the usage of DVS helps us to reduce the computational cost, which facilities the real time performance of our method in future. Furthermore, it is also worth to note that in some challenging scenarios such as driving with sunglasses, the state-of-the-art methods often fail to detect the drowsiness state (impossible to sense the eyes behind the sunglasses) because of the inborn limitation of the sensors e.g., the narrow dynamic range of RGB cameras.

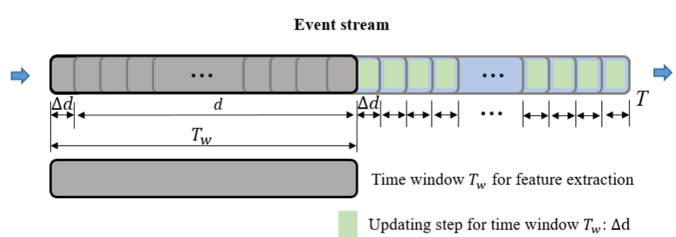


Fig. 11. Sliding time window detection mechanism for real time drowsiness driving detection.

VI. CONCLUSION

In this work, the first event-based drowsiness driving detection system through facial motion analysis is proposed. By using a novel neuromorphic vision sen sor, the proposed work simplifies the traditional vision based detection process as our new sensor is a natural motion detector for the drowsiness driving related motions. The unique properties of DVS inspire us to propose a highly efficient method to recognize and localize the driver's eyes and mouth motions from the event streams. We further design and extract drowsiness-related features directly from these motions to establish the EDDD model. Additionally, an EDDD dataset is provided in this work, the first public dataset dedicated to event-based drowsiness driving detection. Both offline and online experiments are conducted and demonstrate the high efficiency and accuracy of the proposed method. Especially, the proposed method can get robust and high-accuracy performance in corner-case scenarios such as driving with sunglasses or driving at night, which is very challenging for traditional frame-based vision sensors. The preliminary research work shows that neuromorphic vision sensor has the potential to be an alternative sensor for drowsiness driving detection.

In future work, we would like to extend our system to real driving scenario by considering the real-time detection of driver's head from other sensing modalities such as RGB images. As event stream includes no color information, it is difficult to locate and track the eyes and mouth by only using event stream, especially when the driver switches his/her gaze frequently. Thus, developing a fusion system from both RGB and event data is worth exploring.

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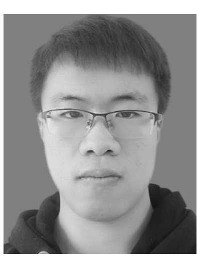

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