Event-based Gesture Recognition with Dynamic Background Suppression using Smartphone Computational Capabilities

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Abstract

This paper introduces a framework of gesture recognition operating on the output of an event based camera using the computational resources of a mobile phone. We will introduce a new development around the concept of time-surfaces modified and adapted to run on the limited computational resources of a mobile platform. We also introduce a new method to remove dynamically backgrounds that makes full use of the high temporal resolution of event-based cameras. We assess the performances of the framework by operating on several dynamic scenarios in uncontrolled lighting conditions indoors and outdoors. We also introduce a new publicly available event-based dataset for gesture recognition selected through a clinical process to allow human-machine interactions for the visually-impaired and the elderly. We finally report comparisons with prior works that tackled event-based gesture recognition reporting comparable if not superior results if taking into account the limited computational and memory constraints of the used hardware.

1 Introduction

This paper focuses on the problem of gesture recognition and dynamic background suppression using the output of a neuromorphic asynchronous camera [8, 22]. It allows for the first time to operate on the true dynamics of observed scenes event per event while only using the mobile phone computation capabilities without requiring connecting to off-board resources (Fig.1).

Figure 1: A neuromorphic camera (an ATIS) (B) is plugged into a smart-phone (A) using an USB link (C), allowing mid-air gesture navigation on the smart-phone.

Neuromorphic event-based cameras offer a novel path to computer vision by allowing to operate at high tem-
poral resolutions at equivalent frame rates at the order of
several kHz at low computational power. They allow for a
new level of performance in real-time vision with a drive
towards more efficient algorithms. Event-based cameras
rely on a new principle that naturally allows all of the in-
formation contained in a standard video stream of several
megabytes to be compressed in an event stream of a few
kilobytes [15, 20].

In this paper we introduce a new method allowing for
outdoor vision-based gesture recognition in real-time us-
ing the only computational power of a mobile phone. It
features a scalable machine learning architecture relying
on the concept of temporal surfaces introduced in [13]
and extending it to operate more robustly. It also tack-
les the difficult problem of dynamic background suppres-
sion by introducing a novel approach in the temporal do-
main to this issue. Furthermore, we introduce a new
data-set of gestures recorded using an event-based cam-
era, that is made available publicly as the neuromorphic
field still lacks data-sets that take full advantage of the
precise timing of event-based cameras. Indeed, in most
available data-sets such as N-MNIST and N-Caltech101
[18] the dynamical properties of the data are artificially
introduced. Even datasets such as the Poker Pips [24] do
not contain intrinsic dynamical properties that could be
used for classification. Compared to previous approaches,
we emphasize the importance of using the information
carried out by the timing of past events to obtain a ro-
bust low-level feature representation. Driven by brain-
like asynchronous event based computations, the method-
ology opens new perspectives for the Internet of Things
(IoT) by operating asynchronously and allocating com-
putational resources only on active parts of the network
thus achieving lesser power consumption and faster re-

2 Related Work

Gesture recognition is an area of research that is quickly
expanding [19, 23] and that currently relies mainly on
two main streams of research. The first one uses wear-
able devices that mainly target specific indoors applica-
tions such as special effects, and are unsuited for outdoor
use. The second stream relies on machine learning tech-
niques coupled with several types of sensors. However,
resource-constrained devices such as smart-phones disal-
low the use of certain technologies, such as vision-based
depth sensors, due to their high energy consumption. This
leads to the use of a wide variety of sensors, such as
the proximity sensor [5] [12] which is readily available on
most smart-phones or even an off-board chip with radio-
frequency capabilities as in [11]. Considering vision-
based approaches, several techniques have been de-
3 Event-based Cameras and the Event-based Paradigm

The Address Event Representation (AER) neuromorphic camera used in this work is the Asynchronous Time-based Image Sensor (ATIS) (see Fig. 1B). Each pixel is fully autonomous, independent and asynchronous, and will only be triggered by a change in contrast in its own field of view. A pixel emits a visual event when the luminance change exceeds a certain threshold, typically 15 percent in contrast. The nature of this change is encoded in the polarity $p$ of the visual event, which can be either ON ($p = 1$) or OFF ($p = 0$), depending on the sign of the luminance change (see Fig. 2). The ATIS has a high temporal precision, in the order of the millisecond, which allows for the capture of highly dynamical scenes. Furthermore, static scenes will produce no output. This results in a low-redundancy, sparse and activity-driven stream of events at the output of such neuromorphic cameras.

$$ e_k = (x_k, t_k, p_k)^T $$

4 Method

4.1 Dynamic Background Suppression

The Dynamic Background Suppression (DBS), aims to remove visual events that are not part of the useful signal, such as background objects. We make use of the native property of high temporal resolution of event-based cameras that allows gestures to generate a higher density of events than background objects as they closer to the camera.

Figure 2: Principle of operation of the neuromorphic camera used in this work. (A) When the change in illuminance of a given pixel’s field of view exceeds a certain threshold, (B) it emits a visual event, which is either "ON" or "OFF" depending on the sign of the change. (C) A given pixel responds asynchronously to the visual stimuli in its own field of view.

Figure 3: Operating principle of the Dynamic Background Suppression (DBS). (A) A gesture is performed in front of the camera, which pixel array is divided into cells. (B) Each cell has its own activity counter that decays over time. (C) Only cells with their activity greater than the mean activity (black dashes) of all cells can spike.
Figure 4: Denoising example of a gesture clip from the NavGestures-walk data-set. The presented gesture is a "swipe
down". Top row is the raw stream of visual events, and the bottom row is the denoised stream, at the output of the 3rd
stage of the cascade presented in this paper. Each snapshot from the top row is made of 10,000 events, and bottom
row contains only the kept events of those 10,000. "ON" events are orange, "OFF" events are black. The filtering lead
to the removal of 83.8% of all events. Even after removing this many events each gesture is still easily recognizable
by the human eye.

The pixel array is divided into a grid of cells. Each cell
c hence contains several pixels and has its own activity
counter noted $A_c$. At each event $e_c^k$ emitted by a pixel
contained in cell $c$ we apply the following formula to up-
date $A_c$:

$$A_c \leftarrow A_c \cdot \exp \left( \frac{-t_c - t_c}{\tau_b} \right) + 1$$  \hspace{1cm} (2)

where $t_c^k$ is the time-stamp of the current event $e_c^k$, $t_c$
the last time a pixel spiked in the cell $c$, and $\tau_b$ a time-
constant set in regards to the pixel array spike-rate. The
average activity $\bar{A}$ of all cells is computed, namely only
the events in cells with $A_c \geq \alpha \bar{A}$ (with $\alpha$ as a scalar to
tune the aggressiveness of the filter) are propagated to the
recognition module. This last stage prevents cells with a
low spike-density, which are considered as background,
from emitting events. An example of the cascade operating
on data from the NavGesture-walk dataset is shown in
Fig. 4

4.2 Time-surfaces as spatio-temporal de-
scriptors

A time-surface [13] is a descriptor of the spatio-temporal
neighborhood of an event $e_k$. We first define the time-
context $T_k(u, p)$ of the event $e_k$ as a map of time differ-
ences between the time-stamp of the current event and the
time-stamps of the most recent events in its spatial neigh-
borhood. This $(2R + 1) \times (2R + 1)$ map is centered on
$e_k$, of spatial coordinates $x_k$. The time-context can be
expressed as:

$$T_k(u, p) = \{ t_k - t | t = \max_{j \leq k} \{ t_j | x_j = (x_k + u), p_j = p \} \}$$  \hspace{1cm} (3)

where $u = [u_x, u_y]^T$ is such that $u_x \in [-R, R]$ and
$u_y \in [-R, R]$. Finally, we obtain the time-surface $S_k(u, p)$ associated
with the event $e_k$, by applying a linear decay kernel of
time-constant $\tau$ to the time-context $T_k$:

$$S_k(u, p) = \begin{cases} 1 - \frac{T_k(u, p)}{\tau}, & \text{if } T_k(u, p) < \tau \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (4)

This gives a low-level representation of a local spatio-
temporal neighborhood. However, as a time-surface is
computed for each new incoming event, overlapping time
surfaces are computed several times leading to resources
wastes. In order to limit this effect, time-surfaces are dis-
carded if they do not contain sufficient information, as this
information will be part of a later time-surface as soon as
a new event is emitted in the spatio-temporal neighbor-
hood. For a time-surface to be considered valid, it must
Figure 5: (A) A moving vertical bar is presented to the event-based camera, which output a stream of visual events. The edges of the bar are ON (white) and OFF (black) events. A ROI is defined around the current event (blue square). (B) The time-stamps of visual events contained in the ROI are decayed using a linear kernel. (C) The resulting extracted time-surface, that encodes both the contour orientation and the dynamic of the motion.

satisfy the following constraint:

$$\sum_{u,p} S_k(u, p) \geq 2R \quad (5)$$

where $R$ is the radius (half-width) of the time-surface. As the event-based camera performs native contour extraction, this ensures that sufficient events to form a valid descriptor can be carried out.

4.3 Event-based hierarchical network

The event-based camera visual events are fed to a network composed of several layers integrating information over increasing temporal scales. As information flows into the network, only their polarities "or new feature planes" are updated. Polarities in the network correspond to learned patterns or elementary features at that temporal and spatial scale. However, as events can be discarded, the network output stream usually contains less events than the input stream, which is an important property that build on the native low output of the event-based camera to lower the computational cost.

4.3.1 Learning prototypes

An iterative online clustering method is used to learn the patterns (hereinafter called prototypes), as it allows to process events as they are received, in an event-based manner. First, a set of $N$ time-surface prototypes $C_n$, with $n \in [0, N-1]$, is created. The $C_n$ are initialized by simply using the first $N$ time-surfaces obtained from the stream of events. Then, for each incoming event $e_k$, we compute its associated time-surface $S_k$. Using the L2 Euclidean distance we compute the closest matching prototype $C_i$ in the bank, which we update with $S_k$ using the following rule:

$$C_i \leftarrow C_i + \alpha_i \frac{S_k \cdot C_i}{\|S_k\| \|C_i\|} (S_k - C_i) \quad (6)$$

with $\alpha_i$ the current learning rate of $C_i$ defined as:

$$\alpha_i = \frac{1}{1 + A_i}$$

where $A_i$ is the number of time-surfaces which have already been assigned to $C_i$. If a prototype $C_i$ has not been triggered by any of the last time-surfaces, it is initialized and forced to learn a new pattern. This prevents badly initialized prototypes to stay unused, and helps them converge to meaningful representations while maintaining always on learning capabilities. It is important to emphasize that compared to the original [13] we show that a linear decay (less computational expensive that the original exponential), combined with the heuristic that allows the suppression of a systematic computation of the time-surfaces allow for massive reduction in computation costs.

4.3.2 Building the network

The set of prototypes can be organized in a hierarchical manner (a set is then called a layer), in order to form a network (see Fig. 6). These layers can have different number of prototypes $N$, radius $R$ (which corresponds to a neuron’s receptive field) and time-constant $\tau$.

The stimulus is presented to the event-based camera (Fig. 6A), which outputs a stream of visual events. A given event $e_m$ of the stream must go through all the layers before the next one $e_{m+1}$ is processed. At each layer, the time-surface $S_m$ associated to $e_m$ is computed (see Fig. 6B), using the previously introduced kernel in Eq.
of time constant $\tau$, and considering a spatial receptive field of side-length $(2R + 1)$. If $S_m$ satisfies Eq. (1), we update the closest prototype $C_c$ using Eq. (6) (see Fig. 6B), and the polarity $p_m$ of $e_m$ is modified so that $p_m = c$, $c$ being the ID of the matching prototype. The polarity now encodes a pattern, and we talk of pattern events instead of visual events for which the polarity corresponds to a luminance change. The pattern event is then fed to the second layer, and processed in a similar manner. The second layer combines patterns from the first layer, thus its prototypes (and so the corresponding polarities) encode more sophisticated patterns. The second layer is therefore able to encode changes of direction in the motion. Once the full network has been trained, meaning that its time-surface prototypes have converged, the learning is disabled: prototypes are not updated using Eq. (6) anymore. The network can now serve as a feature extractor: the polarities of events output by the network will be used as features for classification.

### Table 1: Mean percentage of events left after each the Dynamic Background Suppression for each gesture class.

| Gest. | Mean Event Number | Mean Percentage left after DBS |
|-------|-------------------|--------------------------------|
| down  | 988,901           | 41%                            |
| home  | 2,398,850         | 48%                            |
| left  | 969,014           | 42%                            |
| right | 962,501           | 43%                            |
| select| 1,212,222         | 30%                            |
| up    | 1,110,652         | 44%                            |

### 5 Datasets

We used four datasets, all of them were recorded using a neuromorphic camera: Faces dataset [13], DvsGesture [1] and two novel datasets, NavGestures-sit and NavGestures-walk, tailored to facilitate the use of a smartphone by the elderly and the visually-impaired. NavGestures datasets are publicly available at [url hidden during reviewing for anonymity purposes].

#### 5.1 NavGestures-sit and NavGestures-walk Datasets

The NavGestures-sit dataset was designed to operate on a smartphone using mid-air gestures. The gesture dictionary has only 6 gestures in order to be easily memorable but have also been determined as being the most elementary and sufficient set to operate a mobile phone. Four of them are ”sweeping” gestures: Right, Left, Up, Down. These are designed to navigate through the items in a menu. The Home gesture, a ”hello”-waving hand, can be used to go back to the main menu, or to obtain help. Lastly, the select gesture, executed only using fingers, closing them as a claw in front of the device, and then reopening them, is used to select an item.

The dataset features 35 subjects, 12 being visually-impaired subjects, with a condition ranging from 1 to 4/5 on the WHO blindness scale and 23 being people from the laboratory. The gestures were recorded in real use condition, with the subject sitting and holding the phone in one hand while performing the gesture with their other hand. Some of the subjects were shown video-clips of the gestures to perform, while some others had only an au-
The data description of the gesture. This inferred some very noticeable differences in the way each subject performed the proposed gestures, in terms of hand shape, trajectory, motion and angle but also in terms of the camera pose. Each subject performed 10 repetitions of the 6 gestures. Then all the gesture clips were manually labelled and segmented. We removed clips with a wrong field of view, wrongly executed gestures or that had a device-related capturing issues. The manually curated dataset contains 1,621 clips. The NavGestures-walk dataset contains the same gestures. The main difference being that the users walked through an urban environment while holding the phone with one hand and performed the gestures with the other. The dataset features 10 people from the laboratory that performed several times each of the 6 gestures. The dataset was recorded in uncontrolled lighting condition, both indoor in the laboratory, and outdoor in the nearby streets.

### 5.2 DvsGesture and Faces Dataset

IBM Research released a 10-class (plus a rejection class with random gestures) dataset [11] of hand and arm gestures, performed by 29 subjects under 3 different lighting conditions. The camera is mounted on a stand, and the subjects stand still in front of it, therefore the database is lacking dynamic backgrounds at the core of our work but provides valuable grounds for comparisons. Authors split the dataset into a train database consisting of 23 subjects and a test database consisting of the 6 remaining subjects. The Faces dataset [13], contains clips of the faces of 7 subjects recorded using an event-based camera. Each subject made 24 recordings, resulting in 168 clips. The subjects moved their face while following a dot on a computer screen in a square movement. The dynamic is therefore the same for all subjects, and does not carry any meaningful information for the classification task. The faces dataset does not come with a proposed split between a train and a test subset. This allows us to perform cross-validation (10 random shuffles of train and test subsets) to ensure that the results are solid. As in the original paper, we put 5 examples in the train subset, and 19 the test subset.

### Table 2: Detail of the experiments that were taken on the different datasets.

| ID  | Dataset               | DBS | Grid | Layer 1 | Layer 2 | Classifier | Results |
|-----|-----------------------|-----|------|---------|---------|------------|---------|
|     |                       |     |      | N       | R       | Tau        | N       | R       | Tau        |          |
| E1  | Faces                 |     | 32   | 6       | 5 ms    | k-NN, k = 1 | 96.6%  |
| E2  | Faces                 |     | 48   | 6       | 5 ms    | k-NN, k = 1 | 97.9%  |
| E3  | Faces                 |     | 64   | 6       | 5 ms    | k-NN, k = 1 | 98.5%  |
| E4  | NavGestures-sit ✓     |     | 8    | 2       | 10 ms   | k-NN, k = 7 | 94.5%  |
| E5  | NavGestures-sit ✓     |     | 8    | 2       | 10 ms   | 8        | 2       | 100 ms   | k-NN, k = 7 | 95.9%  |
| E6  | NavGestures-walk ✓    |     | 8    | 2       | 10 ms   |           | 75.9%  |
| E7  | NavGestures-walk ✓    |     | 8    | 2       | 10 ms   | 8        | 2       | 100 ms   | k-NN, k = 7 | 81.3%  |
| E8  | NavGestures-walk ✓    |     | 8    | 2       | 10 ms   |           | 88.7%  |
| E9  | NavGestures-walk ✓    |     | 8    | 2       | 10 ms   | 8        | 2       | 100 ms   | k-NN, k = 7 | 92.6%  |
| E10 | DvsGestures 10cl ✓    |     | 3×3  | 8       | 2       | 10 ms    | 64      | 2       | 100 ms    | k-NN, k = 11 | 96.6%  |
| E11 | DvsGestures 11cl ✓    |     | 3×3  | 8       | 2       | 10 ms    | 64      | 2       | 100 ms    | k-NN, k = 11 | 88.9%  |
| E12 | DvsGestures 11cl ✓    |     | 5×5  | 8       | 2       | 10 ms    | 64      | 2       | 100 ms    | MLP       | 93.1%  |

6 Experiments and Results

In the following experiments we did not take the polarity of visual events into account: we considered that only the illuminance change carries information for these classification tasks, and not the fact that the illuminance increased or decreased. This is because the same gesture can generate either ON or OFF events depending on the skin color, the clothing color or the background. For all classification tasks, the output of end-layers is integrated over time to generate a histogram of activity per feature.
This can then be used as a dynamic signature of the observed stimulus that can then be fed to a classifier (here a nearest neighbor). More sophisticated classifiers can be used, we chose however partly to save power resources a simple methodology but mostly to show that extracted features are strongly capturing the essence of the dynamic signature of the recorded gestures.

6.1 Removing the background on the NavGestures datasets

If subjects are sitting in the NavGestures-sit, they do hold the phone in their hand, which results in movements and unwanted jitters that both generate background activity. In the case of the NavGestures-walk the visual background is even more present as subjects were walking while recording the dataset. Figure 4 illustrates the use of the Dynamic Background Suppression (DBS). Table 1 reports the mean percentage of events left for each gesture class after removing the background. It must be noted that we did not use the DBS on the DvsGesture dataset because it was recorded with a static camera and because the background was static, therefore there is no background to remove. The following parameters were used for the DBS:

- $\tau_b = 300\mu$s
- $\alpha = 2$
- grid size : $3 \times 3$

6.2 Results on the gesture datasets

In our experiments on the gesture datasets (E4 to E11) we tried both 1-layer and 2-layers networks, and also the benefits of the Dynamic Background Suppression on the recognition rate. Two-layers network perform better, as they can handle changes in direction. Also the Dynamic Background Suppression greatly improves the recognition rate, as demonstrated for the NavGestures-walk, increasing the score from 81.3% to 92.6%.

Regarding the DvsGesture dataset, we use the same 2-layer network architecture. The only difference is that we increased the number of prototypes in the second layer because the gestures are more complex, and more prototypes in the end-layer account for more discriminative power.

6.3 Gesture recognition on the smartphone

The whole system, made of the DBS, a 1-layer feature extractor and the recognition module, is implemented on a mobile phone, a Samsung GM-920F, as native C++ code. The event-based camera is directly plugged into the micro-usb port of the mobile phone (see Fig. 1). This prototype was briefly tested by visually-impaired end-users, in real use condition. They were asked to perform certain tasks using the phone, such as sending a pre-written message or play a song. Results of the pre-tests can be found in table 7. It is important to emphasize that some gestures require longer execution time, because it they generate much more visual event that thus require more computation. This is one of the properties of being scene-driven.

6.4 Results on the Faces dataset

Using a single-layer network with a receptive field $R = 6$, $N = 32$ prototypes and $\tau_a = 5$ ms, the scope is to push the system to its limit and inquire whether a single layer is enough to capture the static properties of this dataset. We are able to obtain 96.6% recognition score on this dataset, whereas the original model in [13] performed at 79% using a three-layer architecture, with its end-layer having

| Dataset             | This work | HOTS [13] | IBM [1] |
|---------------------|-----------|-----------|---------|
| Faces               | 98.5%     | 79%       | -       |
| DvsGestures 10 cl   | 96.6%     | -         | 96.5%   |
| DvsGestures 11 cl   | 93.1%     | -         | 94.6%   |
| NavGestures-sit     | 95.9%     | -         | -       |
| NavGestures-walk    | 92.6%     | -         | -       |

Table 3: Comparison of the classification accuracy on event-based datasets.

We also took into account the spatial component of gestures. This is possible because clips of the DvsGesture dataset all have the same framing. We split the pixel array into sub-regions, using a $3 \times 3$ grid. Hence, the final feature is a histogram of size $3 \times 3 \times 64 = 576$. Classification used a nearest neighbor classifier on the histograms. One can observe in table 5 that the system performs in the same range of precision as [11] while being lighter to implement and compute.
Figure 7: Results obtained with visually-impaired end-users on early tests using the prototype. Users were asked to perform different scenarios such as sending a pre-written message. Average correct classification is 78%, however this score is heavily impacted by not-so-good score of the "select" gesture, which is performed in very different ways among users, something we already had reckoned during the dataset creation.

Additional material provides videos of the Dynamic Background Suppression at work and of live gesture recognition on the smartphone.

7 Discussion

In this work, we presented a system that allows to recognize gestures using a smartphone computational capabilities. We also improved drastically the hierarchical network proposed in [13], both for static and dynamic data. The system and methodology allows to truly understand what the network is computing rather than the conventional black-box approach. We can report that the first layers operating on shorter time scales are extracting oriented contours and direction, while the second layers encode change of directions of the same feature. Deeper networks could theoretically encode multiple changes in direction, but given the nature of gestures and the task to be performed there no need to use such networks. We can assess that a 2-layered network is sufficient to handle efficiently any of the considered databases. This is truly the advantage of using time-surfaces that encode in a compact representation both spatial and temporal information. The system also relies on a very small number of meta parameters to tune. We did not require long parameter adjusting processes for all the considered databases. Once the parameters of the network match those of the observed object, the same set can apply regardless to the dataset, and we were able to use the same parameters for all the gestures datasets, while obtaining state-of-the-art accuracy scores on the DvsGestures classification task. We believe this is the first time that time-surfaces were used at their true potential. Indeed, in previous work like HOTS [13] or HATS [25] the decay times used were set to values thousands times higher than the duration of the stimulus. This resulted in time-surfaces that acted as binary frames, instead of truly encoding the dynamic of the scene. This comes as no surprise as considering inadequate time scales uncorrelated with the dynamics of the observed scene will provide low amounts of information and therefore poor recognition rates. Finally, the Dynamic Background Suppression plays a very important role in achieving high recognition rates in a walking situation.

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References

[1] Arnon Amir, Brian Taba, David J Berg, Timothy Melano, Jeffrey L McKinstry, Carmelo Di Nolfo, Tapan K Nayak, Alexander Andreopoulos, Guillaume Garreau, Marcela Mendoza, et al. A low power, fully event-based gesture recognition system. In CVPR, pages 7388–7397, 2017.

[2] Mohammadreza Babaee, Duc Tung Dinh, and Gerhard Rigoll. A deep convolutional neural network for video sequence background subtraction. Pattern Recogn., 76(C):635–649, April 2018.

[3] O. Barnich and M. Van Droogenbroeck. Vibe: A universal background subtraction algorithm for video sequences. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 20(6):1709–1724, 2011.

[4] L. Bretzner, I. Laptev, and T. Lindeberg. Hand gesture recognition using multi-scale colour features, hierarchical models and particle filtering. Proceedings Fifth IEEE International Conference on Automatic Face and Gesture Recognition, pages 423–428, 2002.

[5] Heng-Tze Cheng, An Mei Chen, Ashu Razdan, and Elliot Buller. Contactless gesture recognition system using proximity sensors. In Consumer Electronics (ICCE), 2011 IEEE International Conference on, pages 149–150. IEEE, 2011.

[6] Xavier Clady, Jean-Matthieu Maro, Sébastien Barré, and Ryad B Benosman. A motion-based feature for event-based pattern recognition. Frontiers in neuroscience, 10, 2016.

[7] N.H. Dardas and N.D. Georganas. Real-time hand gesture detection and recognition using bag-of-features and support vector machine techniques. IEEE Transactions on Instrumentation and Measurement, 60(11):3592–3607, 2011.

[8] T Delbruck, B Linares-Barranco, E Culurciello, and C. Activity-driven, event-based vision sensors. In Proc. IEEE International Symposium on Circuits and Systems, 2010.

[9] A. Elgammal, D. Harwood, and L. Davis. Non-parametric model for background subtraction. European conference on computer vision, pages 751–767, 2000.

[10] W.T. Freeman and M. Roth. Orientation histograms for hand gesture recognition. International workshop on automatic face and gesture recognition., 12:296–301, 1995.

[11] Bryce Kellogg, Vamsi Talla, and Shyammath Gollakota. Bringing gesture recognition to all devices. In NSDI, volume 14, pages 303–316, 2014.

[12] Eun Ji Kim and Tae Ho Kang. Mobile device having proximity sensor and gesture based user interface method thereof, June 14 2010. US Patent App. 12/814,809.

[13] Xavier Lagorce, Garrick Orchard, Francesco Gallupi, Bertram E Shi, and Ryad Benosman. Hots: a hierarchy of event-based time-surfaces for pattern recognition. IEEE PAMI, 2016.

[14] Jun Haeng Lee, Tobi Delbruck, Michael Pfeiffer, Paul KJ Park, Chang-Woo Shin, Hyunsurk Ryu, and Byung Chang Kang. Real-time gesture interface based on event-driven processing from stereo silicon retinas. IEEE transactions on neural networks and learning systems, 25(12):2250–2263, 2014.

[15] Patrick Lichtsteiner, Christoph Posch, and Tobias Delbruck. A 128x128 120db 15us latency asynchronous temporal contrast vision sensor. IEEE Journal of Solid State Circuits, 2008.

[16] S. Mitra and T. Acharya. Gesture recognition: A survey. IEEE Transactions on Systems, Man, and Cybernetics,, 37(3):311–324, 2007.

[17] N. M. Oliver, B. Rosario, and A. P. Pentland. A bayesian computer vision system for modeling human interactions. IEEE transactions on pattern analysis and machine intelligence, 22(8):831–843, 2000.

[18] Garrick Orchard, Ajinkya Jayawant, Gregory K Cohen, and Nitish Thakor. Converting static image datasets to spiking neuromorphic datasets using saccades. Frontiers in neuroscience, 9:437, 2015.
[19] Pramod Kumar Pisharady and Martin Saerbeck. Recent methods and databases in vision-based hand gesture recognition: A review. *Computer Vision and Image Understanding*, 141:152–165, 2015.

[20] C. Posch, D. Matolin, and R. Wohlgenannt. A QVGA 143 dB Dynamic Range Frame-Free PWM Image Sensor With Lossless Pixel-Level Video Compression and Time-Domain CDS. *Solid-State Circuits, IEEE Journal of*, 2011.

[21] Christoph Posch, Daniel Matolin, and Rainer Wohlgenannt. A qvga 143 db dynamic range frame-free pwm image sensor with lossless pixel-level video compression and time-domain cds. *IEEE Journal of Solid-State Circuits*, 46(1):259–275, 2011.

[22] Christoph Posch, Teresa Serrano-Gotarredona, Bernabe Linares-Barranco, and Tobi Delbruck. Retinomorphic event-based vision sensors: Bioinspired cameras with spiking output. *Proceedings of the IEEE*, 2014.

[23] Siddharth S Rautaray and Anupam Agrawal. Vision based hand gesture recognition for human computer interaction: a survey. *Artificial Intelligence Review*, 43(1):1–54, 2015.

[24] Teresa Serrano-Gotarredona and Bernabé Linares-Barranco. Poker-dvs and mnist-dvs. their history, how they were made, and other details. *Frontiers in neuroscience*, 9:481, 2015.

[25] Amos Sironi, Manuele Brambilla, Nicolas Bourdis, Xavier Lagorce, and Ryad Benosman. Hats: Histograms of averaged time surfaces for robust event-based object classification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1731–1740, 2018.

[26] Jie Song, Gábor Sörös, Fabrizio Pece, Sean Ryan Fanello, Shahram Izadi, Cem Keskin, and Otmar Hilliges. In-air gestures around unmodified mobile devices. In *Proceedings of the 27th annual ACM symposium on User interface software and technology*, pages 319–329. ACM, 2014.

[27] T. Starner and A. Pentland. Real-time american sign language recognition from video using hidden markov models. *Motion-Based Recognition*, 12:227–243, 1997.

[28] C. Stauffer and W. E. L. Grimson. Adaptive background mixture models for real-time tracking. *IEEE Transactions on Image processing*, 2, 1999.

[29] Pei Xu. A real-time hand gesture recognition and human-computer interaction system. *CoRR*, abs/1704.07296, 2017.