High Speed Event-based Face Detection and Tracking in the Blink of an Eye

Gregor Lenz*, Sio-Hoi Ieng*, Ryad Benosman†
*Sorbonne Université INSERM, CNRS, Institut de la Vision
{1, 2, 3}@upmc.fr
†University of Pittsburgh
Carnegie Mellon
benosman@pitt.edu

Abstract—We present the first purely event-based method for face detection using the high temporal resolution of an event-based camera. We will rely on a new feature that has never been used for such a task that relies on detecting eye blinks. Eye blinks are a unique natural dynamic signature of human faces that is captured well by event-based sensors that rely on relative changes of luminance. Although an eye blink can be captured with conventional cameras, we will show that the dynamics of eye blinks combined with the fact that two eyes act simultaneously allows to derive a robust methodology for face detection at a low computational cost. We show that eye blinks have a unique temporal signature over time that can be easily detected by correlating the acquired local activity with a generic temporal model of eye blinks that has been generated from a wide population of users. We show that once the face is reliably detected it is possible to apply a probabilistic framework to track the spatial position of a face for each incoming event while updating the position of trackers. Results are shown for several indoor and outdoor experiments. We will also release an annotated data set that can be used for future work on the topic.

Index Terms—face detection, event-based, neuromorphic vision

1 INTRODUCTION

This paper introduces an event-based method to detect and track faces from the output of an event-based camera. The method exploits the dynamic nature of human faces to detect, track and update multiple faces in an unknown scene. Although face detection and tracking is considered practically solved in classical computer vision, the use of conventional frame-based cameras does not allow to consider dynamic features of human faces. Event-based cameras record changes in illumination and are therefore able to record dynamics in a scene with high temporal resolution (in the range of 1 µs to 1 ms). In this work we will rely on eye blink detection to initialise the position of multiple trackers and reliably update their position over time. Blinks produce a unique space-time signature that is temporally stable across populations and can be reliably used to detect the position of eyes in an unknown scene. This paper extends the state-of-art by:

• implementing a human eye-blink detection that exploits the high temporal precision provided by event-based cameras.
• detecting and tracking multiple faces simultaneously at µs precision.

The pipeline is entirely event-based in the sense that every event that is output from the camera is processed into an incremental scheme rather than creating frames to recycle existing image-based methodology. We show that the method is inherently robust to scale change of faces by continuously inferring the scale from the combined eyes detection/tracking algorithm. Comparatively to existing image-based face detection techniques such as [19], we show in this work that we can achieve a reliable detection at the native temporal resolution of the sensor without using costly computational techniques. Existing approaches usually need offline processing to build a spatial prior of what a human face should look like or vast amounts of data to be able to use machine learning techniques. The method is tested on a range of scenarios to show its robustness in different conditions: indoor and outdoor scenes to test for the change in lighting conditions; a scenario with a face moving close and moving away to test for the change in scale and finally a scenario where multiple faces are detected and tracked simultaneously. In order to compare performance to frame-based techniques, we build frames at a fixed frequency (25fps) from the grey-level events provided by the event based camera. We then apply a gold-standard face detection algorithm on each frame and the result is used as the ground truth for assessing the event-based algorithm.

2 RELATED WORKS

2.1 Event-based cameras

Event-based vision sensors are a new class of sensors based on an alternative signal acquisition paradigm. Rethinking the way how visual information is captured, they increasingly attract attention from computer vision community as they provide many advantages that frame-based cameras are not able to provide without drastically increasing
computational resources. Redundancy suppression and low latency are achieved via precise temporal and asynchronous level crossing sampling as opposed to the classical spatially dense sampling at fixed frequency implemented in standard cameras.

Most readily available event-based vision sensors stem from the Dynamic Vision Sensor (DVS) [9]. As such, they work in a similar manner of capturing relative luminance changes. As Fig. 1 shows, each time illuminance for one pixel crosses a predefined threshold, the camera outputs what is called an event. An event contains the spatial address of the pixel, a timestamp and a positive (ON) or negative (OFF) polarity that corresponds to an increase or decrease in illuminance. Formally, such an event is defined as the n-tuple: \( ev = (x, y, t, p) \), where \((x, y)\) are the pixel coordinates, \(t\) the time of occurrence and \(p\) is the polarity. Variations of event-based cameras implement additional functionality. In this work, we are using the Asynchronous Time-based Image Sensor (ATIS) [14] as it also provides events that encode absolute luminance information, as does [11]. Here the time it takes to reach a certain threshold is converted into an absolute grey-level value. This representation allows for easier comparisons with the frame-based world.

To compare the output of such cameras with conventional ones, artificial frames can be created by binning the grey-level events. A hybrid solution of event- and frame-based worlds captures grey-level frames like a regular camera on top of the events [3]. Inherently, no redundant information is captured, which results in significantly lower power consumption. The amount of generated events directly depends on the activity and lighting conditions of the scene. Due to the asynchronous nature and therefore decoupled exposure times of each pixel these sensors timestamp and output events with \(\mu s\) precision and are able to reach a dynamic range of up to 125 dB. The method we propose can be applied to any event-based camera operating at sub-millisecond temporal precision as it only uses events that encode change information.

### 2.2 Face detection

The most prevalent group of algorithms for frame-based face detection is based on rigid templates, learned mainly by boosting a high number of low-confidence filters [21]. The most well-known example of this was developed by Viola and Jones in [19]. Another approach is based on deformable part models (DPMs), that models parts of the face separately. [10] has shown that there is still room for improvement for DPMs using improved annotations. The advent of neural networks enables state-of-the-art detectors [20], [3], [18], which rely on intensive computation of static images and needs enormous amounts of data. Although there have been brought forward ideas on how to optimise frame-based techniques for face detection on power-constraint phones, most of the times they have to use a dedicated hardware co-processor to enable real-time operation [16]. Nowadays dedicated chips such as Google’s Tensor Processing Unit or Apple’s Neural Engine have become an essential part in frame-based vision, specialising in executing the matrix multiplications necessary to infer neural networks on each frame as fast as possible.

Blink detection in a frame-based representation is a sequence of detections achieved via matching learned templates frequently provided by Haar cascade classifiers. It is inherently using a face detection mechanism at first and blinks are deduced from the sequence of detection results. Blink characterisation is coarse as they are limited by frame acquisition rate (e.g. 15Hz in [13]). In an event-based approach, we turn the principle inside out and use blink detection as a mechanism to drive the detection and the tracking of faces. Being the first real-time event-based face detector and tracker (to the best of our knowledge), we show that by manually labelling fewer than 50 blinks, we can generate sufficiently robust models that can be applied to different scenarios. The results clearly contrast the vast amount of data and GPUs needed to train a neural network.

### 2.3 Human eye blinks

We take advantage of the fact that adults blink synchronously and more often than required to keep the surface of the eye hydrated and lubricated. The reason for this is not entirely clear, research suggests that blinks are actively involved in the release of attention [12]. Generally, observed eye blinking rates in adults depend on the subject’s activity and level of focus and can range from \(3 \text{blinks}/\text{min}\) when reading up to \(30 \text{blinks}/\text{min}\) during conversation (Table 1).

Fatigue significantly influences blinking behaviour, increasing both rate and duration [6]. Typical blink duration is between 100 – 150 ms [11] and shortens with increasing physical workload or increased focus.

| Activity       | # Blinks per min |
|----------------|------------------|
| reading        | 4.5              |
| at rest        | 17               |
| communicating  | 26               |
| non-reading    | 15-30            |

Table 1

To illustrate what happens during an event-based recording of an eye blink, Fig. 2 shows different stages of the eye lid closure and opening. If the eye is in a static state, few events will be generated (a). The closure of the
eye lid happens within 100 ms and generates a substantial amount of ON events, followed by a slower opening of the eye (c,d) and the generation of mainly OFF events. From this observation, we devise a method to build a temporal signature of a blink. This signature is then used to signal the presence of a pair of eyes in the field of view, hence the presence of a face.

3 METHODS
3.1 Temporal signature of an eye blink
Eye blinks are a natural dynamic stimulus that can be represented as a temporal signature. While a conventional camera is not adequate to produce such a temporal signature because of its stroboscopic and slow acquisition principle, event-based sensors on the contrary are ideal for such a task. The blinks captured by an event-based camera are patterns of events that possess invariance in time because the duration of a blink is independent of lighting conditions and steady across the population. To build a canonical eye blink signature \( A(t) \) of a blink, we convert events acquired from the sensor into temporal activity. For each incoming event \( ev = (x_i, y_i, t_i, p_i) \), we update \( A(t) \) as follows:

\[
A(t_i) = \begin{cases} 
    A_{on}(t_u)e^{-\frac{t_i-t_u}{\text{scale}}} + \frac{1}{\text{scale}} & \text{if } p_i=ON \\
    A_{off}(t_v)e^{-\frac{t_i-t_v}{\text{scale}}} & \text{if } p_i=OFF
\end{cases}
\]

where \( t_u \) and \( t_v \) are the times an ON or OFF event occurred before \( t_i \). The respective activity function is increased by \( \frac{1}{\text{scale}} \) at each time \( t_u \) an event ON or OFF is registered. The quantity scale acts as a corrective factor to account for a possible change in scale, as a face that is closer to the camera will inevitably trigger more events. Fig. 2 on top of the next page shows the two activity profiles for one tile that aligns with the subject’s eye in a recording. Clearly visible are the 5 profiles of the subject’s blinks, as well as much higher activities at the beginning and the end of the sequence when the subject moves as a whole. From a set of manually annotated blinks we build such an activity model function as shown in Fig. 2 where red and blue curve respectively represent the ON and OFF parts of the profile.

Our algorithm detects blinks by checking whether the combination of local ON- and OFF-activities correlates with that model blink that had previously been built from annotated material. To compute that local activity, the overall input focal plane is divided into one grid of 16 by 16 tiles, overlapped with a second similar grid made of 15 by 15 tiles. Each of these are rectangular patches of 19 × 15 pixels, given the event-camera’s resolution of 304 × 240 pixels. They have been experimentally set to line up well with the eyes natural shape. The second grid is shifted by half the tile width and height to allow for redundant coverage of the focal plane.

An activity filter is applied to reduce noise: For each incoming event, its spatio-temporal neighbourhood is checked for corresponding events. If there are no other events within a limited time or pixel range, the event is discarded. Events that pass this filter will update ON or OFF activity in their respective tile(s). Due to the asynchronous nature of the camera, activities in the different tiles can change independently from each other, depending on the observed scene. Each incoming event updates activity for its tile(s) according to Eq. [1].

\[ B(t) = B_{ON}(t) \cup B_{OFF}(t). \]

As part of the model and for implementation purposes, we are also adding the information \( N = \# \text{events} \times \frac{T}{\text{scale}} \), which is normalised by the scale term that reflects the typical number of events triggered by a blink within that last \( T \)ms.

3.1.1 Blink model generation
The model blink is built from manually annotated blinks from multiple subjects. We used two different models for indoor and outdoor scenes, as the ratio between ON and OFF events changes sufficiently in natural lighting. 20 blinks from 4 subjects resulted in an average model as can be seen in Fig. 2. The very centre of the eye is annotated and events within a spatio-temporal window of one tile size and 250 ms are taken into account to generate the activity for the model. This location does not necessarily line up with a tile of the previously mentioned grids. Due to the sparse nature of events, we might observe a similar envelope of activity for different blinks, however the timestamps of when events are received will not be exactly the same. Since we want to obtain a regularly sampled, continuous model, we interpolate activity between events by applying Eq. [1] for a given temporal resolution \( R_t = 100 \mu s \). Those continuous representations for ON (red curve) and OFF (blue curve) activity are then averaged across different blinks and smoothed to build the model. We define the so obtained time-continuous model:

\[ B(t) = B_{ON}(t) \cup B_{OFF}(t). \]

As part of the model and for implementation purposes, we are also adding the information \( N = \# \text{events} \times \frac{T}{\text{scale}} \), which is normalised by the scale term that reflects the typical number of events triggered by a blink within that last \( T \)ms.

3.1.2 Sparse cross-correlation
When streaming data from the camera, the most recent activity within a \( T = 250 \text{ ms} \) time window is taken into account in each tile to calculate the template matching score for ON and OFF activity. However, the correlation score is only ever computed if the number of recent events exceeds \( N \), to avoid costly and unnecessary calculations. To further alleviate computational burden, we harness the event-based
nature of the recording by taking into account only values for which we have received events. Fig. 4 shows an example of a sparse correlation calculation. The cross-correlation score between the incoming stream of events and the model is given by:

\[ C(t_k) = \alpha C_{on}(t_k) + (1 - \alpha) C_{off}(t_k), \]

where

\[ C_p(t_k) = \sum_{i=0}^{N} A_p(t_i) B_p(t_i - t_k), \]

with \( p \in \{ON, OFF\} \). The ON and OFF parts of the correlation score are weighted by a parameter \( \alpha \) that tunes the contribution of the ON/OFF events. This is necessary as, due to lighting and camera biases, ON and OFF events are usually not balanced. The weight \( \alpha \) is set experimentally, typically for indoor and outdoor conditions.

It is important for implementation reasons to calculate the correlation as it is in Eq. 4 because while it is possible to calculate the value of the model \( B(t_m - t_k) \) at anytime, samples for \( A \) are only known for the set of times \( \{t_i\} \) from the events.

If \( C(t_i) \) exceeds a certain threshold, we create what we call a blink candidate event for the tile in which the event that triggered the correlation occurred. Such a candidate is represented as the n-tuple \( eb = (r, c, t) \), where \( (r, c) \) are the coordinates of the grid tile and \( t \) is the timestamp. We do this since we correlate activity for tiles individually and only in a next step to combine possible candidates to a blink.

### 3.1.3 Blink detection

To detect the synchronous blinks of two eyes, blink candidates across grids generated by the cross-correlation are tested against additional constraints for verification. As a human blink has certain physiological constraints in terms of timing, we check for temporal and spatial coherence of candidates in order to find true positives. The maximum temporal difference between candidates will be denoted as \( \Delta T_{\text{max}} \) and is typically 50 ms, the maximum horizontal spatial disparity \( \Delta H_{\text{max}} \) is set to 60 pixels and maximum vertical difference \( \Delta V_{\text{max}} \) is set to 20 pixels. Algorithm 1 summarises the set of constraints to validate a blink. We trigger this check whenever a new candidate is stored. The scale factor here refers to a face that has already been detected.

**Algorithm 1: Blink detection**

```plaintext
1 Inputs: A pair of consecutive blink candidate events 
   \( eb_u = (r_u, c_u, t_u) \) and \( eb_v = (r_v, c_v, t_v) \) with \( t_u > t_v \)
2 if \( (t_u - t_v < \Delta T_{\text{max}}) \) AND
   \( (|r_u - r_v| < \Delta V_{\text{max}} \times \text{scale}) \) AND
   \( (|c_u - c_v| < \Delta H_{\text{max}} \times \text{scale}) \) then
   if face is a new face then
   return 2 trackers with scale = 1
   else
   return 2 trackers with previous scale
3 end
```

### 3.2 Gaussian tracker

Once a blink is detected with sufficient confidence, a tracker is initiated at each detected location. Trackers such as the
ones presented in [7] are used with bivariate normal distributions to locally model the spatial distribution of events. For each event, every tracker is assigned a score that represents the probability of the event being generated by the tracker: \[
p(u) = \frac{1}{2\pi} |\Sigma|^{-\frac{1}{2}} e^{-\frac{1}{2}(u-\mu)^T \Sigma^{-1}(u-\mu)}
\] where \(u = [x, y]^T\) is the pixel location of the event and the covariance matrix \(\Sigma\) is determined when the tracker is initiated and will also update according to the distance between the eyes. The tracker with the highest probability is updated, provided that it is higher than a specific threshold value. A circular bounding box for the face is drawn based on the horizontal distance between the two eye trackers. We shift the centre of the face bounding box by a third of the distance between the eyes to properly align it with the actual face.

3.3 Global algorithm

The detection and tracking blocks put together allow us to achieve the following event-by-event global face tracking Algorithm 2.

Algorithm 2: Event-based face detection and tracking algorithm

1. for each event \(ev(x, y, t, p)\) do
2.  if at least one face has been detected then
3.    update best blob tracker for \(ev\) as in [5]
4.    update scale of face for which tracker has moved according to tracker distance
5.  end
6.  update activity according to [1]
7.  correlate activity with model blink as in [6]
8.  run Algorithm 3 to check for a blink
9. end

4 Experiments and Results

We evaluated the algorithm’s performance on a total of 46 recordings from 10 different people. The recordings are divided into 4 sets of experiments to assess the method’s aptitude in different constraints. Two major sets of recordings were recorded indoors and outdoors. Another set of experiments emphasises the change of scale of the tracked face to show the robustness of the algorithm. Finally, a sequence is showing the algorithm applied to a scene with multiple faces.

In order to evaluate the performance of the proposed algorithm, we obtained ground truth (GT) of the face’s position from an OpenCV implementation of the Viola-Jones algorithm. It is applied to frames created from the grey-level events provided by the ATIS by binning them every 40 ms. This provided conventional grey-level videos with 25 fps at a resolution of 304 x 240 pixels. The software implementation of the algorithm is written in C++ and runs in real-time on an Intel Core i7-7700 CPU.

| number of recordings | % of blinks detected | abs. tracking error [pixel] |
|----------------------|----------------------|-----------------------------|
| indoor               | 21                   | 68.35 ± 7.6                | 5.95 ± 2                     |
| outdoor              | 21                   | 52.3 ± 10.4                | 7.68 ± 2.7                  |
| scale                | 3                    | 62.6 ± 17                  | 5.84 ± 2.2                  |
| multiple             | 3                    | 36.78 ± 10                 | 5.66 ± 2.1                  |
| total                | 48                   | 59 ± 13.4                  | 6.68 ± 2.4                  |

Summary of results for detection and tracking for 4 sets of experiments. % of blinks detected relates to all blinks in one recording, absolute tracking error uses Euclidean distance between proposed face tracking centre and GT bounding box centre.

4.1 Blink detection and face tracking

The threshold set for the correlations to ensure a reliable blink detection is experimentally set to .88. As Table 2 shows, on average 59% of blinks are successfully detected in recordings, in which a true positive is allowed to be detected within a 5 pixels range. Tracking errors relate to Euclidean distance between our face tracker and GT, average tracking error across all recordings is 6.68 ± 2.4 pixel.

A better tuning of the parameters of the event-based camera would increase the number of events output from the sensor. We chose a standard bias configuration that generated a lower number of events that did not affect the method when the user is close to the camera. However if users are far from the camera, the pixel surface of the eye is around 8 pixels width resulting in low activation rates of pixels. It is important to emphasise that this issue is related to the technology used that relied on one of the earliest generations of event-based cameras that has a low resolution of QVGA.

Results show that the blink detection rate does not necessarily have to be 100% as it is used to initialise the trackers, which is always the hardest part in a tracking algorithm and also to correct for drift. Moreover, it should be emphasised that when placing the face tracker after detection, we shift it vertically depending on the distance between the two eyes, as the centre of the face is not between the eyes. This also corrects for the vertical offset between centre of our proposed face tracker and GT.

4.2 Indoor and outdoor sequence

The indoor data set consists of recordings in controlled lighting conditions. As blinking rates are highest during rest or conversation, subjects in a chair in front of the camera were instructed not to focus on anything in particular and to gaze into a general direction. Fig. 5 shows tracking data for such a recording. Our algorithm starts tracking as soon as one blink is registered (a). After an initial count to 10, the subject should lean from side to side every 10 seconds in order to vary their face’s position. Whereas tracking accuracy on the frame-based implementation is constant (25 fps), our algorithm is updated event-by-event depending on the movements in the scene. If the subject stays still, computation is drastically reduced as there is a significantly lower number of events. Head movement causes the tracker to update within \(\mu s\) (b), incrementally changing its location in sub-pixel range. We can conclude that trackers work
Figure 5. Face tracking of one subject over 45s. a) Subject stays still and eyes are being detected. Movement in the background to the right does not disrupt detection. b) When the subject moves, several events are generated reliably enough and if they fail, the next detection will rectify their position.

Subjects in the outdoor experiments were asked to step from side to side in front of a camera placed in a courtyard under natural lighting conditions. Again they were asked to gaze into a general direction, partly engaged in a conversation with the person who recorded the video. As can be expected, Table 2 shows that results are similar to indoor conditions. The slight difference is due to non-idealities and the use of the same camera parameters as the indoor experiments. Event-based cameras still lack an automatic tuning system of their parameters that hopefully will be developed in a future generation of a camera.

### 4.3 Scale change sequence

In 3 recordings the scale of a person’s face varies by a factor of more than 5 from smallest to largest detected occurrence. Subjects sitting on a movable stool were instructed to approach the camera within 25 cm after an initial position and then veer away again after 10 s to about 150 cm. Fig. 6 shows tracking data for such a recording over time. The first blink is detected after 3 s at roughly 1 m in front of the camera (a). The subject then moves very close to the camera and to the left so that not even the whole face bounding box is seen anymore (b). Since the eyes are still visible, this is not a problem for our tracker. However, GT had to be manually annotated for this part of the recording, as the frame-based method failed to detect the face since it is not robust to such a loss of information. The subject then moves backwards and to the right, followed by further re-detections (c).

A 3D-representation of the same recording is illustrated in Fig. 7. The tracker positions of left and right are shown in red and green lines, respectively. It is easy to see how scale relates to the distance between the eyes. 3 screenshots are plotted for the 3 positions in respect to different distances to the camera.

Figure 6. Verifying resistance to scale. a) first blink is detected at initial location. Scale value of 1 is assigned. b) Subject gets within 25 cm of the camera, resulting in a three-fold scale change. c) Subject veers away to about 150 cm, the face is now 30% smaller than in a)

Figure 7. Scale experiment. Detected blinks are marked with black diamonds. As soon as a blink is detected, left (red) and right (green) eye are tracked. a) Subject is about 70 cm in front of the camera. b) Subject gets within 25 cm in front of the camera. c) A blink is detected even though the subject moved about 120 cm away from the camera.

### 4.4 Multiple faces sequence

In order to show that the algorithm can handle multiple faces at the same time, we recorded 3 sets of 3 subjects sitting at a desk talking to each other. No instructions were given, as the goal was to record in a natural environment. Fig. 8 shows tracking data for such a recording. The three subjects stay relatively still, but will look at each other from time to time as they are engaged in conversation or focus a screen. Lower detection rates (see Table 2) are caused by an increased pose variation, however this does not result in an increase of the tracking errors.
more specifically, this would allow us to handle conditions
would also allow for a greater variety in pose variation and
keep the same distances between parts of the face. This
based model of the face as it has been tested successfully in
nose, etc) and by linking them to build a deformable part-
using additional trackers for more facial features (mouth,
occluding elements. This problem however can be mitigated
problem of non detection and for the trackers that are attracted by
the centre blinks next, considerably varying their face orientation when
looking at the other two. c) third subject stays relatively still.

5 Conclusion
The presented method for face detection and tracking is a
novel method using an event-based formulation. It relies on
eye blinks to detect and update the position of faces making
use of dynamical properties of human faces rather than a
purely spatial approach. The face’s location is updated at
μs precision that corresponds to the native temporal resolu-
tion of the camera. Tracking and re-detection are robust to
more than a five-fold scale, corresponding to a distance in
front of the camera ranging from 25 cm to 1.50 m. A blink
seems to provide a sufficiently robust temporal signature
as its overall duration changes little from subject to subject.
The amount of events received and therefore the resulting
activity amplitude varies only substantially when lighting
of the scene is extremely different (i.e. indoor office lighting
vs bright outdoor sunlight). The model generated from an
initial set of manually annotated blinks is proven robust to
those changes across a wide set of sequences. Even so, the
primary goal is not to detect 100% of blinks, but to reliably
track a face. The blink detection acts as initialisation and
recovery mechanism to allow that. In its present form, the
method is mainly sensitive to occlusion for obvious reasons
of non detection and for the trackers that are attracted by
occluding elements. This problem however can be mitigated
by using additional trackers for more facial features (mouth,
nose, etc) and by linking them to build a deformable part-
based model of the face as it has been tested successfully in
Once the trackers are initiated, they could more easily
keep the same distances between parts of the face. This
would also allow for a greater variety in pose variation and
more specifically, this would allow us to handle conditions
when subjects do not directly face the event-based camera.

The blink detection approach is simple and yet robust
even more by learning the dynamics of blinks via techniques
ad hoc to the event-based representation. Techniques such as
HOTS [8] are a promising way for us to reach significant
improvement. Currently the implementation runs on a single
CPU. Due to the asynchronous nature of the input and our
method that adapts to it, it could easily be parallelised across
multiple threads or cores, while computation is still bound
to synchronous processing of instructions and allocating
memory rather than neuromorphic hardware. More impor-
tantly with increasingly efficient event-based cameras pro-
viding higher spatial resolution the algorithm is expected to
increase its performances and range of operations.

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