Abstract

Due to their high temporal resolution and large dynamic range event cameras are uniquely suited for the analysis of time-periodic signals in an image. In this work we present an efficient and fully asynchronous event camera algorithm for detecting the fundamental frequency at which image pixels flicker. The algorithm employs a second-order digital infinite impulse response (IIR) filter to perform an approximate per-pixel brightness reconstruction and is more robust to high-frequency noise than the baseline method we compare to. We further demonstrate that using the falling edge of the signal leads to more accurate period estimates than the rising edge, and that for certain signals interpolating the zero-level crossings can further increase accuracy. Our experiments find that the outstanding capabilities of the camera in detecting frequencies up to 64kHz for a single pixel do not carry over to full sensor imaging as readout bandwidth limitations become a serious obstacle. This suggests that a hardware implementation closer to the sensor will allow for greatly improved frequency imaging. We discuss the important design parameters for full-sensor frequency imaging and present Frequency Cam, an open-source implementation as a ROS node that can run on a single core of a laptop CPU at more than 50 million events/sec. It produces results that are qualitatively very similar to those obtained from the closed source vibration analysis module in Prophesee’s Metavision Toolkit. The code for Frequency Cam and a demonstration video can be found at https://github.com/berndpfrommer/frequency_cam.

1. Introduction

Unlike traditional frame-based imaging devices, event based cameras [14] imitate a biological retina by immediately providing a signal whenever the illumination of a pixel changes by more than a certain threshold. Avoiding frame accumulation results in sub-millisecond latencies [8], avoids transmission of repetitive information, and lowers power consumption. Moreover since each pixel adapts to its individual illumination and emits events based on the logarithm of the photo current, event cameras by design feature a high dynamic range.

These exciting properties have attracted much interest from the research community, an overview of which can be found in Ref. [5]. A great deal of effort has focussed on accomplishing high-level tasks in robotics and computer vision among which are visual odometry [18], event-based classification and object detection [20], object tracking [29] and control [4].

The present work addresses a much more basic task that has received surprisingly little attention: how to detect the frequency of periodically varying signals on a per-pixel level. Often periodic flickering is considered a nuisance signal to be filtered out [28], however there is commercial interest for frequency detection in the context of vibration analysis. In fact Prophesee’s Metavision Source Development Kit (SDK) contains a vibration analysis module to which we will compare (Fig. 1).

At this point it is necessary to discuss more precisely what frequency detection means. For brevity, in the context of this paper frequency generally refers to the lowest frequency present in a periodic signal, also known as the fundamental frequency. Proper detection of the fundamental frequency requires reconstructing the brightness of each individual pixel (c.f. Sec.3.3), storing it in a suitably large buffer, computing its Fourier transform, and finding the lowest-frequency peak in the spectrum. For off-the-shelf hardware this approach is prohibitively expensive in terms of memory and compute resources and yet will still fail in some situations, for example when a high frequency signal is modulated with low frequency. Such periodogram based methods are also a poor match for the neuromorphic paradigm of the camera due to the buffering involved.

Some compromises to the objective must be made so it can be tackled by an asynchronous and light-weight algorithm. It turns out that many simple signals such as square, triangular, or sine waves are repetitions of one monotonically rising and one falling section. In this case one can detect the onset of the falling section when an ON (illumination decrease) event is followed by an OFF (illumination increase) event [3]. The time period between detecting successive transitions can then serve as a proxy for the
The present work improves on the robustness of the baseline by performing an approximate reconstruction of the brightness from the events by means of a digital filter, followed by the detection of zero-level crossings. While detecting zero-level crossings is still by no means the same as finding the fundamental frequency, the approach is substantially more robust to noise events than the baseline. It no longer requires the signal to consist of monotonically rising and falling sections but only mandates that the signal cross the zero level twice per period. Our approach further retains the fully asynchronous and light-weight nature of the baseline, and for some signals allows for more accurate frequency measurements by interpolation of the zero-level crossing times (Fig. 10).

As we turn our attention from frequency detection for a single-pixel to full-sensor frequency imaging we discover:

- the severe limitations imposed on the camera’s performance by finite readout bandwidth,
- how strongly lens flare affects frequency detection in scenes with high dynamic range,
- what is important for an algorithm to produce visually pleasing real-time frequency images and,
- why the baseline algorithm works surprisingly well in a full-sensor setting.

The results of our experiments suggest that frequency imaging can greatly benefit from a hardware implementation close to the sensor.

2. Related Work

Before discussing the few works [3] [6] [7] that use event based cameras for frequency detection or estimation we will set our paper in the context of frequency estimation techniques used in other areas of signal processing.

As already indicated in Sec. 1 we rule out methods based on periodograms that involve Fourier transforms because they require buffering and do not meet our goals with respect to latency and compute effort. For this reason we will limit our attention to so-called parametric approaches which assume the signal to contain at most a few frequencies.

A vast number of parametric algorithms have been developed in the context of Doppler radar technology and for other sensor arrays, one of the most successful ones being the MUSIC [21] algorithm. For single-frequency signals, frequency and phase estimation can be viewed as a linear regression of the phase data [11] [25], allowing for fast and accurate algorithms to extract phase and frequency of a base signal under moderate noise via phase estimation and unwrapping [23]. For all these methods the signal is assumed to be available in its complex “analytic” representation, i.e. as phase and amplitude. Unfortunately event based cameras do not present signals as phase and amplitude but just emit events that can be used for brightness reconstruction to yield at best the (real valued) amplitude. The conversion to an analytic signal requires either an undesirable batch approach such as non-linear least squares (NLS) [2] or the design of an infinite impulse response (IIR) Hilbert transformer, also known as a quadrature filter in the digital signal processing.
literature [1]. We pursued but abandoned this direction. Despite much effort we were unable to design an IIR quadrature filter sufficiently robust to signal noise as observed in our experiments. We suspect this also to be an issue with online NLS-style estimation schemes [12] but we did not explore those.

Based on our negative experience with the Hilbert transform we steered clear of “instantaneous” frequency estimation via the Hilbert-Huang transform [9] which is highly popular for frequency estimation in fields ranging from biomedicine and neuro sciences to ocean engineering and speech recognition. Besides our reservations about the Hilbert transform, the empirical mode decomposition preceding the Hilbert transform appears prohibitively compute heavy for our application.

Frequency estimation is also a central topic for electric power grid monitoring and management. Due to the low frequency (50-60Hz) and because typically only a small number of signals need to be monitored, batch methods like periodograms can be applied. Some online methods [13] look promising but are tested only on relatively low-noise data and for the small frequency band within which the signal is expected to fluctuate. We do however use an idea that is well known in the power grid literature [15]: the accuracy of zero-level crossings can be improved by interpolation. In contrast to Ref. [15] we avoid running a linear regression and simply use the nearest neighbor sample points before and after the crossing.

Pitch detection for audio analysis and speech recognition is often performed with FFT based algorithms, although there are some online approaches as for example Kalman filter based methods [22]. We briefly attempted Kalman filtering for our application but found that updating the filter state and pertaining matrices creates more memory traffic than a typical laptop CPU can handle. Moreover the Kalman filters employed are nonlinear which raises question as to their stability under large noise.

The amount of literature published on frequency detection with event based cameras is quite limited. Among the earlier works is research on blinking LED marker detection in Ref. [3]. The authors outline an algorithm to find which if any of a set of frequencies is present in a signal. Their key idea of detecting signal peaks via polarity transitions is what we refer to as the baseline method in Sec. 3.2. In contrast to our work they know beforehand what the frequency spectrum looks like, but then have to deal with the thorny issue of interference between signals of multiple frequencies. The authors use the transition from ON to OFF events which we confirm to have less jitter than the transition from OFF to ON events. Curiously this fact was overlooked by the later work of Ref. [6] who perform frequency detection based on the OFF to ON transition (their Fig. 4). Like in the present work, Ref. [6] creates a frequency image of the spinning propellers of a quad rotor, but unlike us they do not use a digital filter and present an FPGA implementation whereas our algorithm runs on a CPU. Except for some time averaging of the estimated frequency and using the OFF/ON instead of the ON/OFF transition, Ref. [6] algorithm in their Fig. 3 is comparable in complexity to our baseline method (see Sec. 3.2) and although their work predates ours by four years we believe that with a carefully optimized implementation this could have been done in software already back then, in particular since their ATIS camera has a 304x240 resolution whereas our camera has 640x480 pixels.

Other related work on per-pixel temporal analysis for event based cameras is focused on filtering out periodic signals rather than detecting them. Ref. [28] develops a comb filter in a continuous-time approach, but in this case the frequency is assumed to be known, whereas our goal is to detect the frequency in the first place.

Similar in spirit to our work is the incremental Fourier analysis of event based camera signals in Ref. [19]. There the emphasis too is on exploiting the neuromorphic, asynchronous nature of the camera during frequency analysis. In contrast however, Ref. [19] performs a spatial frequency analysis whereas here the focus is on temporal frequency detection. We could not find a way to transfer their ideas efficiently from the equidistant spatial domain to the irregularly spaced time domain.

The digital filter we propose in Sec. 3.3 and implement on the host side operates in event time, meaning it does not utilize the wall clock time stamps that the camera provides along with each event. Such circuits are known [26] as asynchronous digital signal processors and have been realized in hardware already in the early 1990s [10]. This opens the possibility of implementing our proposed filter in hardware close to the sensor without adding the complexity of an additional clock.

3. Method

3.1. Notation

Following the convention of Ref. [5] a pixel’s brightness $L$ is defined to be the logarithm of its photo current $I$:

$$L = \log(I) . \quad (1)$$

Changes in brightness are signaled by events $e_k = (t_k, p_k)$ where $k$ is the event index, $t_k$ the time stamp, and $p_k \in \{-1, +1\}$ is the polarity of the event.

A brightness increase by more than a threshold $C_{ON}$ is signaled with an ON event of polarity $p_k = +1$, whereas a brightness decrease by more than $C_{OFF}$ will result in an OFF event of polarity $p_k = -1$:

$$\Delta L_k = p_k C_{ON/OFF} . \quad (2)$$
To simplify the notation the customary pixel location $x_k$ for the event is omitted since in this work no spatial filtering is performed. One must bear in mind though that the thresholds $C_{ON/OFF}$ vary from pixel to pixel [27] similar to fixed pattern noise in a frame based camera.

### 3.2. Baseline

For simple signals consisting of one monotonically rising and falling section each per cycle the period of the signal can be found without resorting to reconstructing the brightness [3], [6]. As shown in Fig. 2 (top panel) for the example of a 50Hz square wave signal it is sufficient to record the elapsed time whenever the event polarity changes.

Measuring the signal period by detecting the time of successive OFF to ON event transitions as proposed in Ref. [6] yields much less accurate results than detecting the transition between successive ON to OFF events. This was already noted in Ref. [3] but is here quantitatively shown in the lower panel of Fig. 2 where the ON/OFF transition period has a standard deviation of $\sigma = 1.1\text{us}$ (the time stamp accuracy of the camera is 1us!), whereas using OFF/ON transitions yields $\sigma = 260\text{us}$. The underlying reason for this is most likely that before the first ON event the pixel’s photo current has fallen to very low levels which leads to long response times as documented for the DVS sensor ([8], section 3.1).

Obviously the baseline algorithm is highly efficient and fully asynchronous. We find it to be surprisingly robust when the camera is used in its default bias configuration or when the fundamental frequency of the signal is very high (c.f. Sec. 4.1.3). This is owed to the low pass behavior of the sensor’s photo receptor and source follower [8] which largely filters out higher frequencies such that when the remaining signal reaches the comparator it only produces one ON sequence and one OFF sequence of events per cycle.

### 3.3. Reconstruction by Digital Filtering

While the baseline method is simple and fast it fails for signals that have more than one ON and OFF section per cycle such as the one shown in Fig. 3. Such signals are more likely to be encountered when the sensor biases are tuned for low latency and the sensor’s region of interest (ROI) is reduced.

To address the baseline’s shortcoming, the following approach is proposed:

- reconstruct the brightness approximately by means of a digital filter,
- detect when the reconstructed signal crosses zero from above.

This method is significantly more robust to noise and will correctly detect the fundamental period in many situations where the baseline does not.
The simplest way to reconstruct brightness is to start from Eqn. (2) and to assume \( C_{ON} = C_{OFF} = 1 \):

\[
L_{naive}(t) = \sum_{k|t_k \leq t} p_k
\]  
(3)

As the middle panel of Fig. 3 shows, \( C_{ON} = C_{OFF} \) is a poor assumption that leads to drift in the reconstruction. Not only are \( C_{ON} \) and \( C_{OFF} \) sensor parameters that can be separately configured, but they also change with the overall illumination level and from pixel to pixel [14]. Furthermore we find the ratio of ON to OFF events to vary with the frequency of the time-varying light signal (Fig. 13) and to fluctuate over time, rendering a calibration difficult. Said fluctuations cause the reconstructed signal shown in the bottom panel of Fig. 3 to trend during the time period shown although the thresholds \( C_{ON/OFF} \) have been adjusted to remove any drift over the full duration of the sample. These observations suggest reconstructing the brightness by performing local detrending and integration first, followed by a suitable high pass filter to remove any DC component (see again bottom panel of Fig. 3).

This is exactly what the proposed digital IIR filter does. Before describing the filter however a brief digression regarding sampling and time stamps is necessary. Typically digital filters are based on data points obtained by sampling at regular time intervals, but an event based camera provides samples only when the brightness of a pixel changes by more than \( C_{ON/OFF} \). The digital filter presented here takes as input directly the event polarity \( p_k \in \{-1, +1\} \) of event \( k \). This also constitutes uniform sampling but in event time, not in wall clock time. Thus the filter ignores all time stamps \( t_k \). In fact time stamps are only taken into consideration later when zero-level crossings are detected (Sec. 3.4). Our event time based method is in contrast to the filtering performed in [28] which operates in continuous time. Since the filter does not make use of any time stamps its output is invariant to the (wall clock) time scale, i.e. the frequency of the signal.

As motivated earlier, the first stage of the filter will locally detrend the input signal. This is equivalent to subtracting the moving average polarity \( \bar{p} \) from the polarity \( p_k \) itself:

\[
\Delta \tilde{L}^{(det)}_k := p_k - \bar{p}_{k-1}
\]  
(4)

where \( \bar{p}_k \) is the moving exponential average with a mixing coefficient \( \alpha \in [0, 1] \):

\[
\bar{p}_k := \alpha \bar{p}_{k-1} + (1 - \alpha) p_k .
\]  
(5)

In (4) we have set \( C_{ON} = 1 \) and \( C_{OFF} = 1 \) because the absolute scale of the signal does not matter for detecting zero-level crossings and the averaging in (5) will compensate for the \( C_{ON/OFF} \) ratio being different from unity. The output of the first filter stage is the detrended change in brightness \( \Delta \tilde{L}^{(det)} \), where the tilde indicates that this is an approximate reconstruction.

Next, the detrended changes in brightness are integrated up:

\[
\tilde{L}_k^{(det)} = \tilde{L}_{k-1}^{(det)} + \Delta \tilde{L}^{(det)}_k
\]  
(6)

and passed through a high-pass filter to remove the DC component and remaining low-frequency noise as discussed earlier:

\[
\tilde{L}_k = \beta \tilde{L}_{k-1} + \frac{1}{2} (1 + \beta)(\tilde{L}_k^{(det)} - \tilde{L}_{k-1}^{(det)})
\]  
(7)

\[
= \beta \tilde{L}_{k-1} + \frac{1}{2} (1 + \beta) \Delta \tilde{L}_k^{(det)} .
\]  
(8)

Evidently the integration in (6) can be skipped since the high-pass filter (7) immediately takes differences of its input. The particular way the filter parameter \( \beta \in [0, 1] \) is introduced in (7) ensures that the high pass has unit gain at the Nyquist frequency \( \omega = \pi \).

Combining (4), (5) and (8) and utilizing the \( z \)-transform well known from the digital signal processing literature [16] to (9):

\[
Y(z) = \sum_{n=-\infty}^{\infty} y_n z^{-n} .
\]  
(10)

Under this transform Eqn. (9) becomes:

\[
\tilde{L}(z) = H_\alpha(z) H_\beta(z) P(z)
\]

\[
H_\alpha(z) = \left( \frac{z - \frac{1}{\alpha}}{z - \alpha} \right)
\]  
\[
H_\beta(z) = \frac{1}{2} \frac{z(1 + \beta)}{z - \beta} .
\]  
(11)

The transfer function \( H(z) = H_\alpha(z) H_\beta(z) \) connecting input polarities \( P(z) \) to reconstructed brightness \( \tilde{L}(z) \) is the product of a high pass \( H_\alpha(z) \) and a low pass \( H_\beta(z) \) component which together form a band pass, see Fig. 4.

A few words are in order as to why \( H_\alpha(z) \) acts as high pass and \( H_\beta(z) \) as a low pass. Although the averaging procedure in (5) suggests that \( H_\alpha \) may be a low pass, it is in fact a high pass due to the first term on the r.h.s. of (4) being an all pass from which then the low pass is subtracted. Likewise, despite \( H_\beta \) involving the high pass filter (7) it also contains the integration (6) which is intrinsically a low pass operation, resulting in \( H_\beta \) actually having low pass characteristics.

Since each sample corresponds to a single event, it is more intuitive to think of the filter in terms of the cut-off
Similar design considerations as for relationship between cutoff frequency and $\alpha$ its maximum. Substituting $z$ defined to be the frequency where the cutoff period $T_{\text{cut}}$ period $T_{\text{cut}} = 2\pi/\omega_{\text{cut}}$ rather than the cutoff frequency $\omega_{\text{cut}}$, and to consider a signal to consist of $N_{\text{period}} = N_{\text{ON}} + N_{\text{OFF}}$ events. To preserve the fundamental frequency of the original signal one should first set $\alpha$ such that the cutoff period $T_{\text{cut}}$ for the $H_\alpha$ high pass is larger than $N_{\text{period}}$. The cutoff frequency of $H_\alpha$ depends on $\alpha$, and is defined to be the frequency where $|H_\alpha|^2$ has dropped to half its maximum. Substituting $z = \exp(j\omega)$ into (11) yields the relationship between cutoff frequency and $\alpha$:

$$\alpha = \frac{1 - \sin(\omega_{\text{cut}})}{\cos(\omega_{\text{cut}})} .$$

An analogous procedure can be used to find the relationship between $\beta$ and the cutoff frequency for the low-pass $H_\beta$, which again is where the signal power is attenuated by half:

$$\beta = (2 - \cos(\omega_{\text{cut}})) - \sqrt{(2 - \cos(\omega_{\text{cut}}))^2 - 1} .$$

Similar design considerations as for $\alpha$ apply to the choice of $\beta$: the cutoff frequency of the low pass filter $H_\beta$ should be high enough to just let the signal pass while not being any higher to avoid damping the summation process in (8) that is crucial to the brightness reconstruction. A reasonable choice is then setting the cutoff frequency for $H_\alpha$ and $H_\beta$ to be equal, i.e. a single cutoff period $T_{\text{cut}}$ is chosen for both high and low pass filters. Since $\omega_{\text{cut}}$ is usually well smaller than one and since both (12) and (13) happen to have the same Taylor series expansion to second order $\alpha = 1 - \omega_{\text{cut}} + \frac{1}{2} \omega_{\text{cut}}^2 + O(\omega_{\text{cut}}^3)$ in practice this implies $\alpha = \beta$ such that $H$ has a double pole on the real axis at $z = \alpha$.

Fig. 5 shows the result of filtering the signal from Fig. 3 with different cutoff periods. To achieve good reconstruction both ON and OFF event sections must be reconstructed properly so in practice a conservative choice is keeping $T_{\text{cut}}$ a factor of two larger than the signal period implied by the larger of $2N_{\text{OFF}}$ and $2N_{\text{ON}}$:

$$T_{\text{cut}} = 4 \max(N_{\text{OFF}}, N_{\text{ON}}) .$$

The orange line in Fig. 5 demonstrates that picking $T_{\text{cut}}$ in this way is indeed a good tradeoff between accurately reconstructing the original signal and filtering out low-frequency components.

### 3.4. Finding Zero Level Crossings

Once the approximate reconstruction is complete the zero level crossings can be detected and the signal period derived from that. As Fig. 2 clearly shows, for the baseline method the OFF to ON transition gives much more accurate period estimates than the ON to OFF transition. This carries over to the reconstructed signal as well so we only consider the level crossing from above to below zero when measuring the period. One can then assign the first event time stamp after the level crossing to be the time of the level crossing or linearly interpolate between the two events straddling the zero crossing. Such interpolation schemes are commonly used for power line frequency estimation [15] where the signal has low noise but high accuracy estimates are desired. Figure 6 visualizes these two different methods of measuring the period along with the baseline approach. The top panel shows the reconstruction of a square wave, the bottom of a triangle wave where the logarithm of the current going through the illuminating LEDs was ramped up and down linearly.

### 3.5. Dark Noise Filter

When operating the camera under “fast (single pixel)” bias settings (see Tab. 1) the sensor emits a large number
Figure 6. Three different ways of measuring the signal period: 1) baseline (green) measuring the time between successive ON to OFF transitions, using the time stamp of the first OFF event, 2) filtered (red) taking the time stamp of the first event after zero level crossing from above, 3) interpolated (black), taking the straight-line interpolated time between the events before and after the zero level crossing. The top panel shows the reconstruction for a square wave, the bottom for a triangle wave, both at 100Hz.

Figure 7. When tuned to “fast (single pixel)” bias settings (Tab. 1) the sensor emits dark noise events with a distinct temporal signature: first an event occurs followed after some time by a pair of OFF/ON events that occur in rapid succession, typically within less than 15us. The top panel shows the raw noise event polarities, the bottom the approximate reconstruction. Such noise events thwart any frequency analysis and need to be filtered.

Figure 8. Approximate reconstruction of a 1 Hz square wave signal with (bottom panel) and without (middle panel) dark noise filtering.

e.g. by more than 15us. The latter test will avoid filtering out genuine high frequency signals. Since the spacing in arrival times of the noise OFF/ON events are found to approximately follow an exponential distribution with a mean arrival period that is much larger than 15us, only a small number of noise events will slip through the filter. Note that this dark noise filter utilizes timestamps and is completely unrelated and separate from the digital filter presented in Sec. 3.3.

Noise filtering is particularly beneficial for low frequency signal detection as demonstrated in Fig. 8. Note that the dark noise filtering alters the ratio of ON to OFF events because more noise events occur when the light is being switched off. However the digital filter described in Sec. 3.3 will readily compensate for such an imbalance so long as it does not change abruptly with time.

While the noise reduction in Fig. 8 looks quite impressive, some qualifying statements are necessary.

1. The noise arises only when the sensor bias settings are tuned for high speed operation on a single pixel, not for reasonable full-sensor bias settings.

2. It shows the greatest benefits for detecting low frequency signals, but for such signals there is no reason to tune the sensor biases for high speed. One can however argue that the dark noise filter does increase the captured frequency range of the sensor without requiring changes to the bias settings.

3. Since the filter does not produce output until three subsequent events have occurred it introduces a lag of potentially unbounded length in wall clock time. This can be difficult to deal with when requiring to synchronize
on wall clock time during readout, i.e. when transitioning from neuromorphic to von Neumann computing.

4. Experiments

In this section we will show how the methods presented in Sec. 3 work in practice and what their strengths and weaknesses are. We also use the opportunity to showcase the practical difficulties encountered regarding readout saturation and lens flare.

All experiments are performed with a CenturyArks SilkyEvCam model EvC3A, employing a third-generation Prophesee sensor with VGA 640x480 resolution and a maximum bandwidth of 50 million events/sec (Mevs). For the single pixel datasets and the guitar frequency imaging a Kowa LM35HC 35mm lens is used. All other recordings are obtained with a Computar M0814-MP2 lens. Data is collected and processed on an HP Omen 15 (AMD Ryzen 7 4800H 2.9GHz) laptop with a ROS2 driver building on the Metavision 2.3.2 SDK.

To reduce noise level and avoid camera bandwidth saturation the default programmable bias settings of the SilkyEVCam tune the front end source follower to act as a low pass with a fairly low cutoff frequency, making it difficult to analyze signals above about 1kHz. For this reason different bias settings are used to extend the usable frequency range of the camera as listed in Tab. 1.

4.1. Single Pixel Experiments

In this section a series of different experiments are presented that show how the filter performs versus the baseline. To avoid sensor readout bandwidth saturation the ROI hardware feature of the sensor is used to restrict the activity to only the center pixel \((x = 319, y = 239)\). The camera is pointed at a white surface that is illuminated by six LEDs positioned behind the camera and controlled by a MOSFET based switch which is in turn controlled by a Teensy 4.1 board running at 600MHz CPU frequency. The illuminated surface, LEDs, and lens are enclosed in a lightproof box to ensure that no stray light affects the experiments.

To facilitate comparison the test signals generated with the Teensy board are deliberately picked to be simple enough so the baseline algorithm works, i.e. signals such as those shown in Fig. 3 are avoided. For the square and triangle wave signals (Sec. 4.1.1) the default bias settings (c.f. Tab. 1) are sufficient.

4.1.1 Square Wave

The first test signal is a square wave, i.e. the illuminating LED is abruptly switched on and off. The signal’s reconstruction is shown (at 100Hz) in the top panel of Fig. 6. Notice that although the change in illumination is abrupt, the events spread out over almost the entire signal period.

Reconstruction and signal period measurements are performed for test frequencies of 10Hz, 100Hz, and 1000Hz (see Fig. 9). The camera is operated with default bias parameters for which the sensor front end starts attenuating the signal strongly already at 1kHz, reducing the number of ON events per cycle from 50 (at 10Hz) to 48 (at 100Hz) to about 6 (at 1kHz). To within 0.1us all three methods arrive at the same estimates for the mean: 100.002ms, 10.0002ms, and 1.0000ms. What causes the small over estimation of the period is not clear. The jitter is quite similar as shown in Fig. 9. For 10Hz and 100Hz the baseline has the smallest jitter because the measurement start is triggered only by the very first OFF event of the cycle which occurs near maximum illumination and happens exactly when the light is switched off. For 1kHz this is no longer the case due to the finite sensor front end bandwidth. The jitter increases substantially and interpolation is now favored because it relies on two events (one before, one after the zero level crossing).

4.1.2 Triangle Wave

The experiments in section 4.1.1 are now repeated for a triangle wave for which the reconstruction is shown in the lower panel of Fig. 6. Via pulse width modulation at
146kHz - well above the sensor’s front end low pass frequency - the controller ramps the logarithm of the illuminating LED current up and down linearly. Since in contrast to the square wave the light is not switched off suddenly the occurrence of the first OFF event is less well localized in time and consequently the jitter is much higher (compare to Fig. 9), rendering reconstruction and interpolation beneficial already at 100Hz.

### 4.1.3 Frequency sweep

By default the SilkyEV Cam used here boots up with bias parameters that are tuned for full-sensor operation, where excessive noise events can easily saturate the sensor readout bandwidth. Such conservative settings don’t allow for testing the limits of camera and frequency detection algorithm. Therefore the camera is now tuned for speed with the “fast (single pixel)” settings as listed in Tab. 1 [17], and the ROI is again restricted to the center pixel.

With these camera settings the dark noise filter described in Sec. 3.5 is essential for recovering the signal frequency. The Teensy controller is programmed to sweep through the frequencies exponentially from 1 Hz to 125 kHz and back by first doubling, then halving the frequency every 10 cycles.

As Fig. 11 shows in the bottom panel both the baseline and the filter-based algorithm ($T_{cut} = 25$) can correctly detect across the entire frequency range, albeit the baseline lacking robustness at lower frequencies due to its susceptibility to noise events, and the filter failing at the transition from 67 kHz to 125 kHz due to the rapid change in the ratio of ON to OFF events. For details see Fig. 12.

#### 4.2. Scaling from Single Pixel to Full Sensor

As has been shown in section 4.1, with aggressive bias settings the SilkyEV Cam can be used to detect frequencies over a range of almost five orders of magnitude. However this feat is only possible if the ROI is set to a single pixel. When using the full sensor the dark noise alone already generates sufficiently many events to exceed the 50 Mevs bandwidth of the sensor readout, leaving no choice but to revert to more conservative bias settings. In this section we show that even with default bias settings sensor readout speed is of critical importance for frequency detection.

Unfortunately the manufacturer of the sensor (Prophe-
see) could not disclose more details regarding internals of the readout electronics but we observe that when bandwidth saturates, the events delivered by the SDK are largely in order of monotonically increasing timestamps and with row-major pixel layout. In other words the events arrive as a dense stream from the top left to the bottom right image corner. If every pixel fires, the sensor resolution of 640 x 480 and the bandwidth limit of 50Mev/s imply that every pixel is updated a little fewer than 163 times per second. By the Nyquist theorem the maximum detectable frequency is thus about 81Hz.

In practice the dropping of events due to bandwidth saturation affect the detection already at lower frequencies since events do not arrive equidistant in time, in particular for a square wave signal. Fig. 13 shows an approximate reconstruction ($T_{cut} = 25$) of a 64Hz square wave for the center pixel when just the center pixel is active, when a ROI of 256x256 is configured, or when the full sensor is active. The bottom panel of Fig. 13 demonstrates why even the most robust of algorithms considered here (the baseline) fails to detect the correct frequency. As Fig. 14 shows, frequency detection is already affected at an ROI of 256x256 which comprises just 20% of the sensor surface. Note that all statistics shown in Fig. 14 are derived solely from the center pixel, i.e. the deterioration is due to “cross talk” from other pixels as they compete for readout bandwidth.

The sensor readout bandwidth limits thus profoundly affect the frequency range that can be detected when operating in full sensor mode. Fig. 15 shows an example of the maximum achievable frequency range when observing LEDs driven by a square wave. The frequencies start at...
16Hz and double every time to reach 4096Hz, thus covering about two orders of magnitude compared to the almost five orders of magnitude possible in a single-pixel scenario. For these tests the sensor bias tunings were set to “fast (LEDs)” as shown in Tab. 1. Although only roughly 4% of pixels are active and about 2.5% produce valid frequency detections the readout bandwidth utilization is already at close to 50%.

Fairly strong intensity light is required to elicit events at high frequencies, leading to lens flare that could not be eliminated despite experimenting with several high quality lenses. The frequency image from Fig. 15 was ultimately obtained with a Computar M0814-MP2 8mm 1:1.4 lens with fully open aperture. To reduce interference between the light coming from different LEDs the intensity of each LED was adjusted to account for the low-pass filtering characteristics of the front-end photo receptor circuits. Note that the image is in focus and the LEDs are all the same diameter. The size apparent size difference and visible blur are due to the remaining lens flare mentioned earlier. We also find lens flare originating from high-frequency LEDs to interfere with frequency detection for the low-frequency LEDs as any residual high frequency signal will be detected while the low-frequency LEDs are switched off. Thus the high dynamic range of the event camera not only allows it to detect flickering pixels at widely varying brightness levels but also renders lens flare much more pronounced in dark regions near a flickering light.

The top of Fig. 15 is obtained by using the filtering equation 9 but no dark noise filtering is necessary for the “fast (LEDs)” bias setting. For comparison the bottom image shows a frequency analysis using Prophesee’s Metavision toolkit. More details regarding frequency images follow in Sec. 4.3.

### 4.3. Visualizing frequencies

Much like a thermal imaging camera fascinates by instantly visualizing hot and cold objects in the environment, so the event camera can visualize frequencies over the whole field of view. This is accomplished by running the period estimation algorithm from Sec. 3.3 for each pixel followed by a frequency image readout step at fixed time intervals. Except for the necessarily frame-based readout for display, this approach remains fully asynchronous.

As mentioned in Sec. 4.2 using the whole sensor requires bias settings that severely degrade the range of detectable frequencies. Under default settings the sensor’s front-end circuit filters out high frequency components of the original signal, making it less likely to encounter signals of the form shown at the top of Fig. 3. Rather, when visualizing vibrations or periodic motion as they occur in natural scenes most signals only have a single ON/OFF transition per period and as such do not benefit from the use of the digital filter described in Sec. 3.3 over the baseline method. In the context of frequency visualization, improved frequency accuracy as it can be obtained by interpolating the time when the signal crosses through zero (cf Sec. 3.3) is also irrelevant because such an improvement is hardly visible in a color-coded frequency image. For frequency visualization, other criteria matter more:

- fast detection of a frequency in the acceptable range, preferably before even a full period has passed,
- rapid timeout detection when a pixel no longer produces events, and
- holdover of pixels that have missed events for one or more periods.

The first two criteria are important to preserve edges of fast moving objects and to avoid trailing ghost pixels. To this
end we modify and augment the filter-based approach from Sec. 3.3 as follows:

- If a pixel has no period assigned to it yet, the time of a zero crossing from below or above is used to establish a half period by subtracting the time of the previous transition of opposite sign. This will establish a period estimate as soon as possible.

- A period estimate based on a half period will be replaced by one from a full period as soon as same-sign transitions are available. This means that periods can also be measured between zero level crossings from below as opposed to the more accurate measurements via zero crossings from above.

- A pixel’s period estimate is timed out (deemed invalid) after no events have been received for $n_{timeout}$ full periods. We use $n_{timeout} = 2$ for all experiments presented here.

Note that a pixel only times out when period estimates are read out (the frequency image is generated), so no extra timers have to be maintained to remove inactive pixels. Although strictly the baseline method is sufficient for frequency imaging, we nevertheless deploy the digital filter with $T_{cut} = 5$ to show that filter is computationally efficient and its response is sufficiently fast.

Visualizing periodic signals across the full sensor has attracted enough industry interest for Prophesee to develop a closed-source software solution for this. Their MetaVision toolkit provides the analytics module (FrequencyMapAsyncAlgorithm) which we will use as a reference for qualitative comparison. The detailed workings of this module are not documented, but it only takes two non-obvious parameters: $\text{filter\_length}$, which is the number of times the same period must be measured before outputting an event, and $\text{diff\_thresh\_us}$ which is the maximum period difference allowed between two consecutive periods to be considered identical. For the experiments conducted here we set $\text{diff\_thresh\_us}$ to 100us and $\text{filter\_length}$ to one to avoid trailing ghost images for moving objects.

Fig. 1 shows the frequency image of a flying quad rotor with 6in propellers spinning at about 7500 rpm. Since a propeller has two blades this translates to frequencies of around 250Hz. The top part of Fig 1 is obtained by our method with $T_{cut} = 5$, the bottom with Prophesee’s vibration analysis tool at a readout frequency of 100Hz. The camera is observing the quad rotor from below, with bias settings as listed in Tab. 1 under “fast (quad rotor)”. Although the analysis covers the full sensor, for display purposes the image is cropped to 242 x 281 pixels. Evidently our method produces images very similar to the ones from Prophesee’s module. One can clearly see how the quad rotor is spinning the props at different speeds to generate torque for attitude control.

A second demonstration of the algorithm is presented in Fig. 16. It shows the vibrating strings of a nylon string guitar in open-D tuning (D-A-D-F#-A-D) recorded with the camera in default bias settings. Again our frequency image is very similar to the one produced by the Metavision SDK module albeit we capture the 73Hz frequency of the top most string more accurately. The thin band of double frequency at the center of the string is due to the string passing twice through the center during each period.

While Fig. 16 shows that it is possible to obtain frequency images of instruments it must be mentioned that detecting the vibrations of the high note strings requires favor-
able experimental conditions. For instance the thin strings of a steel string guitar produce hardly any signal. Even the nylon strings demand strong illumination, in this case direct full sunlight at shallow angle with a matte black paper covering the guitar’s sound board to minimize reflection and shadow. The shadow of the strings is still visible at the bottom right corner of the image and on the fretboard at the top right.

5. Runtime Performance and Implementation

The digital filter and zero-level crossing detection presented in Sec. 3.3 can be implemented efficiently in C++ to run at 75 Mev/s on a laptop class AMD Ryzen 4800H CPU clocked at 2.9GHz. Since the camera’s maximum event rate is 50 Mev/s this allows for real-time frequency imaging under full load. The filter itself requires only one multiply and two fused multiply-add instructions per event which for modern CPUs is a very modest compute load. When eliminating all memory access by implementing the filter in registers we find the floating point arithmetic itself to only take about 2.5ns, i.e an implied rate of about 400 Mev/s.

However, as is often the case when implementing neuromorphic algorithms on general purpose CPUs, the real bottleneck is memory access. The full state required is 21 bytes: two 4-byte float variables for lagged \( \tilde{L} \), one byte for the lagged polarity, two 4-byte float variables for the previous zero level crossing times from above and below, and one 4-byte float variable with the current period estimate. Padding inflates the 21 bytes to 24 bytes of state per pixel, or 7MB total which fits just into the 8MB L3 cache of the CPU. Updating the filter state requires two 4-byte load operations for the lagged \( \tilde{L} \) and one 4-byte load for the lagged polarity and the same number of store operations. When zero-level crossings are detected additional load/store operations are required to read and update the times of last zero level crossings and the current period estimate. Typically these variables are already in cache after the filter update because of the CPU’s 64 byte cache line. Nevertheless they consume additional cache memory and due to the fairly random access pattern of event updates performance suffers substantially once the entire state no longer fits into the CPU cache. For our particular CPU however the cache size is sufficient so long as 4-byte float variables are used as opposed to 8-byte double variables.

Note that memory access would not be as important an issue for a GPU based implementation due to the typically large amount of fast memory available there.

6. Conclusion

In this work we explore the task of using an event based camera to find and visualize the fundamental frequency of time-periodic signals in a scene. We show that a combination of aggressive bias tuning, dark noise filtering, and an efficient digital IIR filter can reliably detect frequencies across five orders of magnitude up to 64kHz when restricting the region of interest (ROI) to a single pixel. We compare our digital IIR filter to a simple baseline method and determine under which conditions the use of a filter can achieve more robust and accurate frequency estimates. For full sensor frequency imaging we find the limited readout bandwidth responsible for greatly reducing the capabilities of the camera, suggesting substantial benefits for circumventing bandwidth limitations via an on-camera hardware based solution. Furthermore in high-contrast scenes we find frequency images to be marred by strong lens flare due to the high dynamic range of the camera.

Our open source FrequencyCam imaging algorithm is found to produce frequency images that are very similar to Prophese’s vibration analysis module. The full source code for our ready-to-use ROS node and all data sets used for this paper are accessible under a permissive license at https://github.com/berndpfrommer/frequency_cam.

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