# Rapid Light Flash Localization in SWIR using Compressed Sensing

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Abstract: A high-resolution single pixel camera for long range imaging in the short-wave infrared has been evaluated for the detection and localization of transient light flashes. The single pixel camera is based on an InGaAs photodiode with a digital micromirror device operating as a coded aperture. Images are reconstructed using compressed sensing theory, with Walsh-Hadamard pseudo-random measurement matrices and fast Walsh-Hadamard transform for localization. Our results from experiments with light flashes are presented and the potential use of the camera for muzzle flash detection and localization is discussed.

## 1 INTRODUCTION

The primary signal modalities used to detect snipers are acoustic signal, optical signal from the muzzle flash (visual and IR) and pre-shot laser retro-reflection from the optical sight. In the visual spectrum, the muzzle flash can be extremely weak and hard to detect, especially in daylight and in particular with signature suppressors mounted. The MWIR range (3 - 5 µm) would therefore be seen as the best choice for a hostile fire indication (HFI) system (Trzaskawka et al., 2010; Kastek et al., 2011). The MWIR range is however associated with larger size, weight, power requirements and cost (e.g. higher SWaP-C). Systems operating in the short-wave infrared (SWIR) bands 0.8 - 1.7 µm and 1.1 - 2.5 µm have advantages of potentially lower SWaP-C. The former SWIR band is usually preferred due to the availability of uncooled InGaAs FPAs in this spectral range. An example of the spectral distribution of a 50 caliber gun and images of a sniper rifle at 1000 meters in SWIR and MWIR can be seen in Figure 1.

This paper presents an initial concept of an HFI and sniper sight optics detection system, using Compressive sensing (CS) and a low cost single pixel camera (SPC) with a background subtraction method implemented. Because a very fast photo diode collects the light in the SPC, the temporal resolution of the muzzle flash is not limited by the frame rate. SWIR images of a scene, including the sniper, can be generated while it also can detect and localize fast events such as muzzle flashes. Also, the unique temporal signature of the flash can be measured directly in the detector signal, thus suppressing false alarms which is important for an operational system. Background reduction is performed directly on the raw data with data captured just before or after the fast event, making the data of the flash even sparser. Because the data of the flash is highly sparse, reconstruction of the image is possible using TVAL3 (Total Variation Augmented Lagrangian Alternating Direction Algorithm). Restoration of the image to locate the flash is performed after it is detected and discriminated, thus minimizing the power usage. The system may also be used for optics (or cat's eye) detection if a laser is irradiating the scene, which means that a sniper may be detected and localized pre-shot. (Trzaskawka et al., 2010; Brännlund et al., 2013) This functionality is to some degree demonstrated in the paper, when a small reflector is irradiated with a 1550 nm laser. It may also be possible to find the distance to the target by measuring the time-of-flight of the reflection, but this functionality is not demonstrated as the focus of this paper is on muzzle flash detection. The temporal signature of a muzzle flash in various spectral bands can be seen in Figure 2. As can be seen, the flashes in SWIR are typically less than 1 ms long (Svensson et al., 2011).

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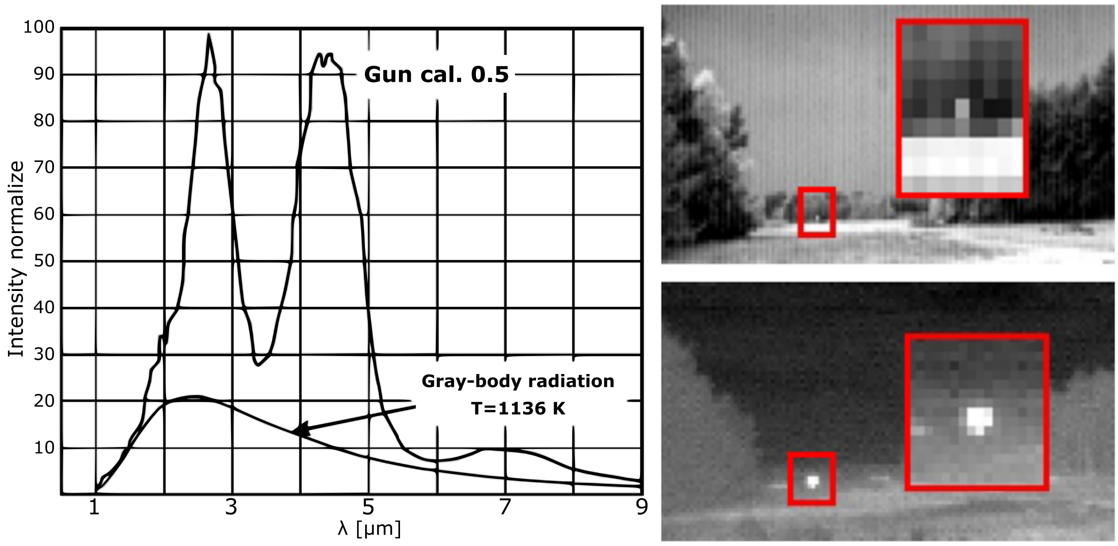


Figure 1: Left: The spectral distribution from a secondary flash. The weapon has a caliber of 0.5 (barrel length 36 in). (Trzaskawka et al., 2010) Top right: Muzzle flash from a sniper rifle at 1000 meters recorded in SWIR (0.8-1.7 μm). Bottom right: Same flash in MWIR (3-5 μm). The red rectangles show enlargements at the rifle position (Krieg et al., 2016).

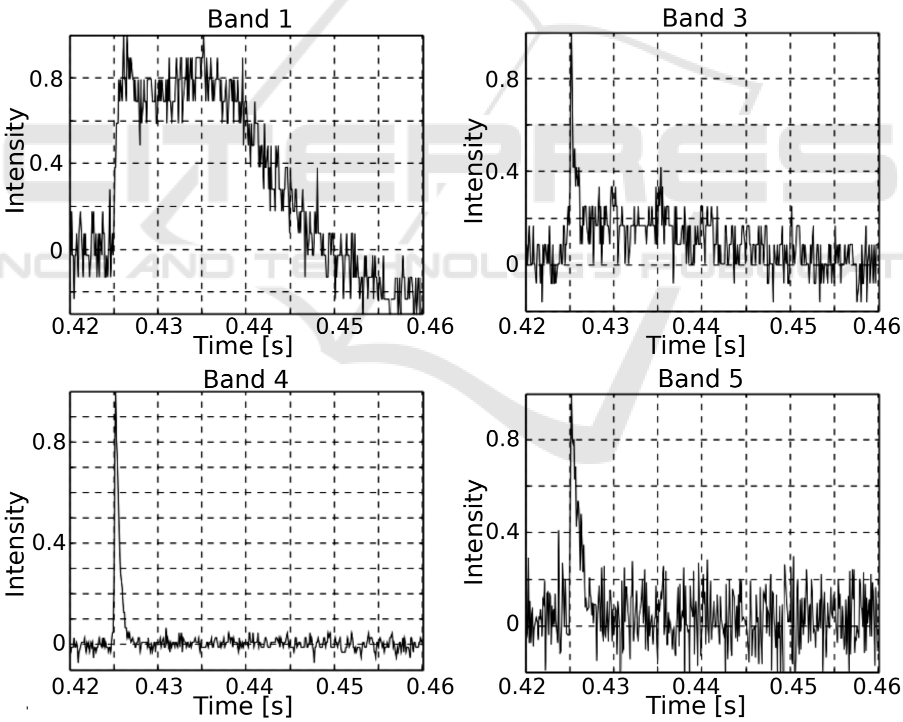


Figure 2: The intensity recorded for a 7.62 cal gun for multiple spectral bands, shown during a 40 ms duration and normalized to the peak value. Band 1 is 0.35 - 0.65 μm, band 3 is 1.46 - 1.79 μm, band 4 is 2.13 - 2.57 μm and band 5 is 3.0 - 4.80 μm. In the 0.35 - 0.65 μm band, only scattered light from the sun and the flash itself was observed (Svensson et al., 2011).

## 2 RELATED WORK

In (Brännlund et al., 2013), a combined hostile fire and optics detection system was tested, using a laser illuminator and a high speed FPA camera in SWIR. In (Krieg et al., 2016), a system using 19 single element detectors to detect muzzle flashes was demonstrated. Additionally, two acoustic sensors were integrated to reduce false alarms. Gil Tidhar proposes a hostile fire indication (HFI) system with two FPA sensors, the first operating in SWIR and the second one in the visible band. With this solution sun-glints and other light sources such as car headlamps can be cancelled out, as the spectra of such sources is typically different to that of a muzzle flash (Tidhar et al., 2009). Trzaskawka et al. presents an initial concept of a cooled electro-optical sensor unit in MWIR for sniper detection purposes and discuss the characteristics of muzzle flashes (Trzaskawka et al., 2010).

Conventional cameras capture the scene by measuring the light at each of the thousands or millions of pixels. In Compressed Sensing (CS), a relatively small number of measurements from the scene is combined with sparse reconstruction procedures to recover an image using only a single or a reduced number of pixel detectors. CS exploits the fact that natural images are compressible or sparse in some basis and therefore only a few measurements relative to the image resolution are needed (sub-Nyquist) to reconstruct the image. Two constraints must be fulfilled in order to utilize CS sampling: the image information needs to be compressible and the measurement matrix need to be incoherent with the sparse transform. The first constraint is fulfilled because it is known that natural images are compressible, using for example JPEG or JPEG2000 compression algorithms. The second constraint is fulfilled using a measurement matrix with a random characteristic. In CS, a high resolution image can be acquired at sub-Nyquist sampling rates while using smaller, cheaper and lower bandwidth components but with the expense of a longer acquisition time compared to standard cameras (Wakin et al., 2006; Takhar et al., 2006; Takhar et al., 2008).

In (Chen et al., 2017) a method to detect light flashes in raw data using a CS-based single pixel camera (SPC) and a sliding window calculation process is presented. They succeed in detecting 25 ms anomalies with an intensity 4 times higher than the background. In previous work Brännlund et al. presented an SPC in SWIR which can detect and localize light flashes from a minimal number of measurements and discuss a muzzle flash detection system using a high speed DMD (Brännlund et al., 2019).

## 3 SINGLE PIXEL CAMERA ARCHITECTURE

Our platform consists of a digital micromirror device (DMD) (Vialux V-7000, $1024 \times 768$, 22.7 kHz) and a large area detector InGaAs photodiode (Thorlabs PDA20C/M, 0.8-1.7 μm). The light from the "active" micromirrors is collected by a "light bucket" - the detector and a 50 mm fixed focal length lens (f/1.4, 0.8-2.0 μm). A single plano-convex lens (Thorlabs, f=200 mm, D=75mm, 1.05-1.7 μm) focusing the scene onto the DMD, see Figure 3. A visual spectrum reference camera is also mounted viewing the DMD to simplify focusing of the system.

The single pixel sensor captures the scene by measuring the light intensity focused onto the detector reflected from the DMD (Digital Micromirror Device), or another SLM (Spatial Light Modulator). The DMD can quickly change patterns to obtain new measurements. $M$ measurements are sampled to reconstruct an image with $N$ pixels, where $M \ll N$. Each element in the measurement matrix is encoded as one or zero (or negative one, with two sensors) which corresponds to the individual DMD mirror state. The CS sampling model is defined as

$$\mathbf{y} = \Phi\mathbf{x} + \varepsilon, \tag{1}$$

where $\mathbf{x}$ is the scene considered as an image rearranged as a one-dimensional array with $N$ pixels, $\mathbf{y}$ is the sampled signal with $M$ measurements, $\Phi$ is the measurement matrix and $\varepsilon$ is the noise. CS states that $M$ can be relatively small compared to $N$, where the number of measurements needed to reconstruct an image depends on the sparsity of the image. Using an SPC where noise contaminates the signal and the scene may not be completely stationary, the number of measurements needed will increase in proportion to the noise and the dynamics in the scene. Permutated Sequence Ordered Walsh-Hadamard matrix (WHM) are used as measurement matrices, which replaces matrix multiplication in Equation 1 with the fast Walsh-Hadamard transform (FWHT). The FWHT is both faster than matrix multiplication and eliminating the need to store the measurement matrices in computer memory. WHM has approximately the same characteristics and properties as an independent and identically distributed (i.i.d.) random matrix but generally needs a higher number of measurements for exact reconstruction of the image. Research has however shown that there is no significant loss in recovery of the image relative to the i.i.d. random measurement matrix (Cai Zhuoran et al., 2013). The total variation (TV) based TVAL3 is used for image reconstruction. Natural images often contain sharp edges

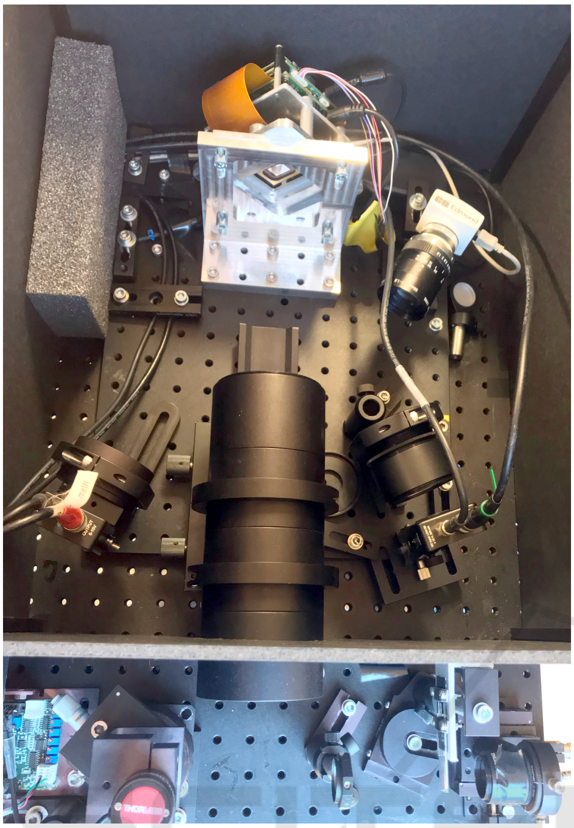

Figure 3: The single pixel camera architecture used in this work. The optics, DMD, reference camera, the single pixel sensor and laser are shown.

and piecewise smooth areas which the TV regularization algorithm is good at preserving. The main difference between TV and other reconstruction algorithms is that TV considers the gradient of signal to be sparse instead of the signal itself, thus finding the sparsest gradient (Li, 2010).

The SPC architecture is also built with an optional secondary detector which measure the complement of the first sensor. Previous research show that similar reconstruction results can be achieved with approximately half the number of patterns compared to one sensor. The research also show that the reconstruction became more stable with dynamics in the scene and vibrations on the camera itself compared to only one sensor. In summary, by using two sensors, the information of the scene sampled is doubled while the noise increases by $\sqrt{2}$ in the combined signal. The benefit of using two sensors in the context of light flash localization is that on average a detector only sees half of the light event per DMD pixel. If it is desired to identify the signal based on a signature, half of the information is lost, but can be complemented using the other detector (Oja and Olsson, 2019).

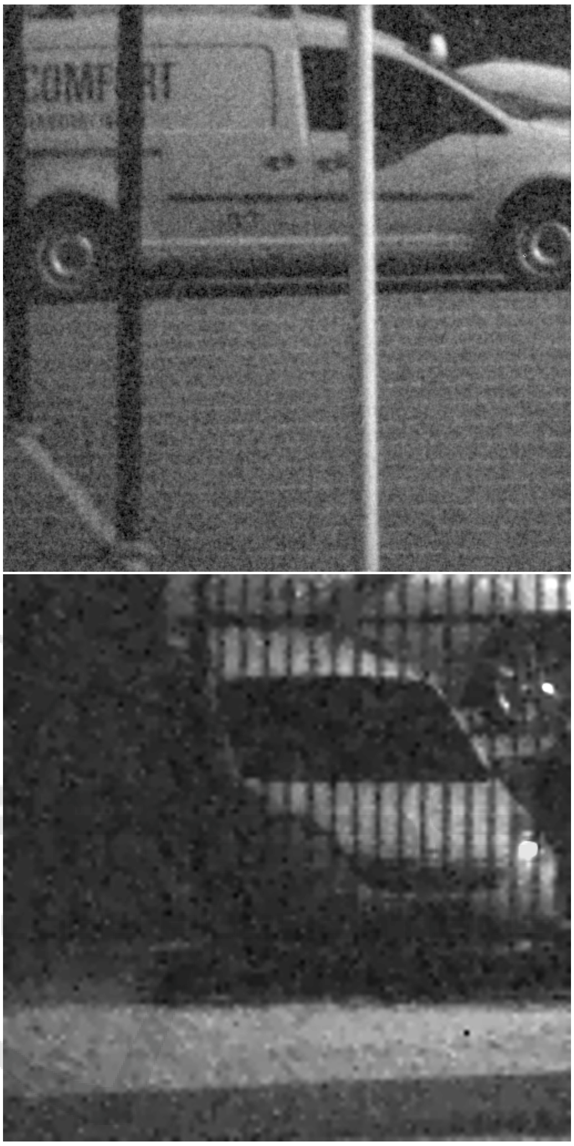

Figure 4: Two images of cars at 512x512 (top) and 256x256 (bottom) pixel resolutions at 350 m. Subsampling ratios are 30% and 40%, respectively. In the bottom image a fence can be seen in the foreground (seen as thin horizontal lines).

## 4 TARGET DETECTION AND LOCALIZATION SYSTEM

The localization systems and target application described in this article rests on an edge case of CS theory and is enabled by the high speed DMD pattern rate. The spatial resolution of the signal to be located is bound to the temporal resolution (the length of the signature) by

$$M \geq k \log(N/k), \tag{2}$$

where $k$ is the number of "pixels" the light flash is visible in and $M$ is the minimum number of patterns required to reconstruct the signal without noise (Takhar et al., 2008). The minimum temporal length of the light flash is

$$t \geq \frac{M}{\text{DMD pattern rate}}, \tag{3}$$

which for example means $t \sim 0.3 - 1.0$ ms, depending on the pixel spread in $32 \times 32$ resolution. In Equation 2 it is assumed that the only information in the signal is the light flash, in order to extract the signal a method with background reduction was implemented which is described in Section 4.1. With the help of the background reduction, in principle, all background information from static objects in the scene is removed, while dynamic information in the scene that has a longer temporary signature than the light phenomenon can be filtered out. After the background reduction, the signal is analyzed by a detection algorithm. The detection algorithm can for example use a matched filter to compare the background reduced signal against a known signature, which is described in Section 4.2. Only if a match with high probability is found the signal is reconstructed for localization. In the localization step, different reconstruction methods can be used depending on the signals temporal length and pixel spread, which is described in Section 4.3.

## 4.1 Background Subtraction

The background reduction has been implemented by repeating a fixed number of patterns on the DMD during the measurement. The number of patterns in the repeating window is set to double the temporal length of the light phenomenon. It is desirable that the window is as small as possible so that potential dynamics in the scene is keept to a minimum. From the measured data $\mathbf{y}$, a new vector is created that contains background-reduced data by calculating the residual between two corresponding patterns according to,

$$\mathbf{y}_{\rho(i)} = |\mathbf{y}_i - \mathbf{y}_{i+w}|, \tag{4}$$

where $\mathbf{y}_\rho$ is the background reduced signal and $w$ is the number of patterns in the window. Assuming that a light flash has occurred in one of the windows the equation can be expanded to

$$\begin{aligned}\mathbf{y}_{\rho(i)} &= |\mathbf{y}_i - \mathbf{y}_{i+w}| \\ &= |(\mathbf{y}_{\delta(i)} + \mathbf{y}_{\beta(i)} + \varepsilon_{(i)}) - (\mathbf{y}_{\beta(i+w)} + \varepsilon_{(i+w)})|,\end{aligned} \tag{5}$$

where $\mathbf{y}_\delta$ is a pattern with a light flash, $\mathbf{y}_\beta$ is background information of the scene and $\varepsilon$ is the noise, assumed to be additive white Gaussian noise. With the relative small time frame between $\mathbf{y}_{\beta(i)}$ and $\mathbf{y}_{\beta(i+w)}$ (e.g. 1.76 ms, with window size of 40 @ 22.7 kHz) we can assume,

$$\begin{aligned}\mathbf{y}_{\beta(i)} &\simeq \mathbf{y}_{\beta(i+w)} \Rightarrow \\ \mathbf{y}_{\rho(i)} &= \mathbf{y}_{\delta(i)} + \varepsilon_{(i)} - \varepsilon_{(i+w)} \\ &= \mathbf{y}_{\delta(i)} + \varepsilon_\Delta.\end{aligned} \tag{6}$$

The only components after the background reduction is the signal of interest and combined noise, as seen in Figure 5a. The combined noise affect the $\sigma_\varepsilon$ (standard deviation) of the reduced signal by a factor of $\sqrt{2}$ compared to the linear signal. The system can also be complemented with a second detector which samples the compliment of the first detector in the scene, which can be seen in Figure 5b. The advantages of using two detectors is that the measurements can be combined in order to get the envelope of the whole light flash, which increases the likelihood of a successful detection and localization even with lower SNR. Alternatively using two sensors with different wavelengths corresponding to two known spectrums of the target and therefore are more robust to natural occurring light phenomenon and thus reducing false positives.

## 4.2 Light Flash Detection

Detection of light flashes can be performed by thresholding the background-reduced signal, which can be done without reconstructing an image of the scene. The temporal signature of the fast event can also be compared with the known signature of the desired light flash, separating it from other natural events using a matched filter. Given the temporal resolution that the signal can be sampled (at least an order of magnitude faster than the DMD pattern rate), it might even be possible to distinguish between unique light flashes depending on length and characteristic envelope. As seen in Figure 5c, the light flash envelope is revealed with basic signal processing techniques such as moving mean even in noisy signals.

## 4.3 Scene Reconstruction

When a desired light flash has been detected the background reduced signal of interests is cut out and reconstructed using a suitable method. The sparse background-reduced signal during the flash (acquired using only a few patterns) can be restored to an image using TVAL3. If the method is successful a noisy image will be restored, where the brightest pixel is located at the position of the light flash. Test on

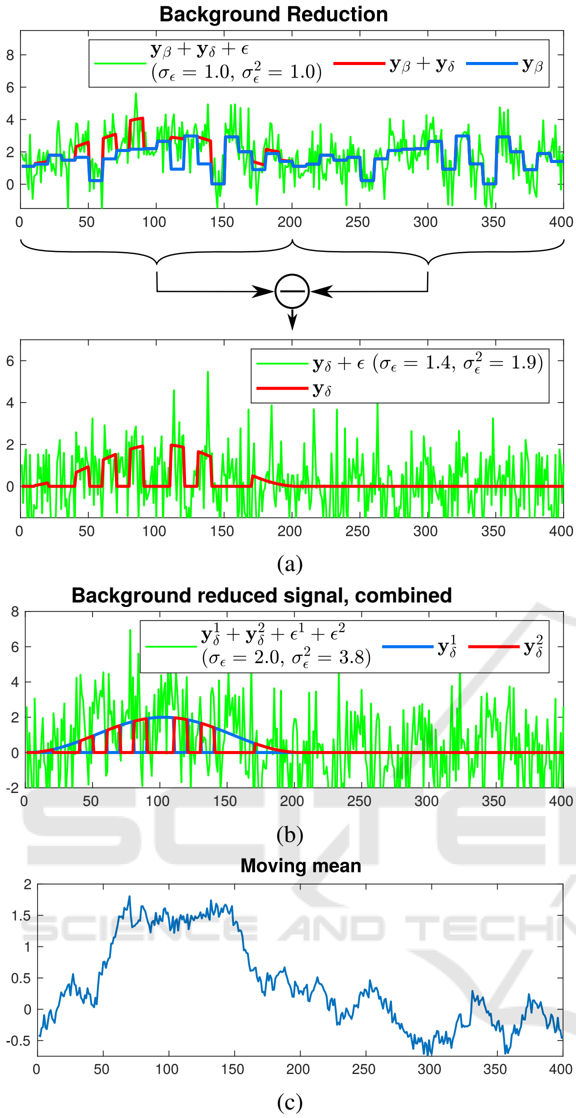


Figure 5: In (a) top plot the simulated signal with the components broken apart for clarity, blue line is the information from the background in the scene which is repeated after 200 samples, red is information from a light flash (represented as half period of $\sin^2$, indices 0-100) added to background, green line is background, light flash and added noise. (a) bottom is the background reduced signal. In (b) the combined background reduced signal from two detectors is plotted. (c) shows plot of moving mean of the combined signal in (b).

simulated light flashes show that the strongest reconstructed pixels using TVAL3 was the same pixels as only using the inverse FWHT (IFWHT). Therefore, only the IFWHT is used in the reconstruction and localization. The difference between using TVAL3 i.e. CS-reconstruction and IFWHT is that TVAL3 will suppress false positives i.e reconstruct a finer picture, but it does not change the strongest initial guesses given by the IFWHT which is performed at the beginning of the TVAL3 algorithm.

## 5 EXPERIMENTS

To link the research and the experimental set-up to a concrete problem, we choose to simulate a muzzle flash. Munitions flashes, such as gunshots, explosions, missile launches and kinetic ammunition are high-speed phenomena with time durations from sub-milliseconds to a fraction of a second. Standard cameras with typical frame rates of 30 or 60 Hz are not fast enough for detection of snipers and the problem therefore requires non-standard high-speed imaging solutions. But even if the frame rate is high, it still needs to be significantly higher than 1 kHz to resolve the temporal signature, which is normally beyond the capability of most sensors (Svensson et al., 2011). The flash can be detected with such a device, but it may only be resolved in a single frame thus making it susceptible to false alarms. The high data rate of a FPA is also a problem, because the algorithm needs to analyse all the pixels in each frame and compare it to the previous one to detect the fast rise in pixel value. By comparison the SPC with a high speed pattern rate ($>$ 22 kHz) is both capable of resolving the temporal signature ($>$ 100 kHz DAQ) and locate the flash.

To simulate the muzzle flash, a small reflector was placed in the scene and was irradiated by a pulsed laser placed next to the SPC. The laser parameters in the measurement was 7 W @ 1550 nm, 20 mrad divergence, 10 Hz pulse repetition frequency and a pulse length of 1 ms (a square wave with a duty cycle of 1%). The simulation of the muzzle flash is far from perfect. The size of the reflector (Ø7 cm) may be much smaller compared to a real muzzle flash and the temporal and spectral signatures will also differ to some extent. We simulated a $\sim$ 1 ms muzzle flash that at the current pattern rate is resolved by approximately 22 patterns. Given Equation (2), and factoring in nose and dynamics in the scene (which increases $M$) and possible pixel spread ($1 \leq k \leq 4$) the resolution was set to $N = 32 \times 32$. In all the measurements (images), the FOVs are increased by binning the micromirrors, so the resolution of the patterns used was $1024 \times 1024$ and effective reconstructed resolution of $32 \times 32$. The reflector was placed in different environments and at different length from the camera. In the results presented in Section 6, the reflector was placed on a three trunk ca. 350 m from the camera. This scene contains dynamics in the form of grass and branches from the trees that moves with the wind, turbulence as well as natural lightning from the sun.

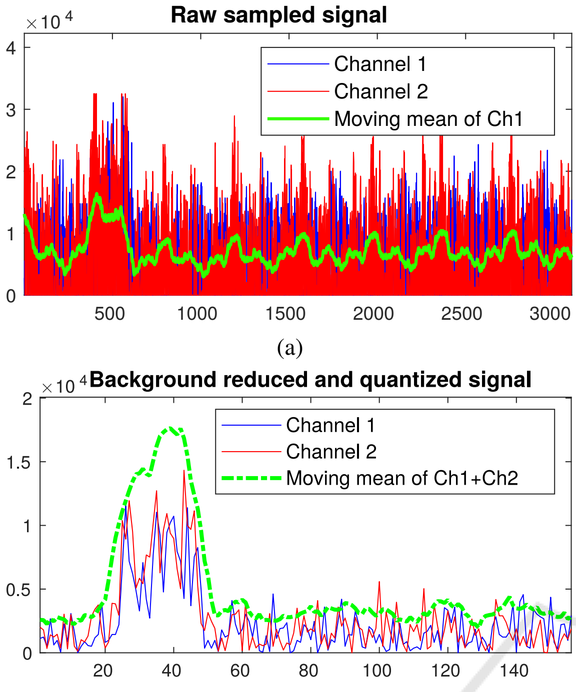


Figure 6: (a) Raw sampled signal with light flash (notice the repetitions for each window which shows that the background is static). (b) Background reduced and quantized signal from (a), by combining the signals and calculate moving mean the light flash envelope becomes clear.

## 6 RESULTS

An example of the signals when an outdoor reflector is pulsed with the laser can be seen in Figure 6. With adequate SNR and number of patterns are sampled during the pulse, the result will be a dark image with the brightest pixel at the position of the light source.

In Figure 7, the restored $32 \times 32$ image (using 20 patterns) of the simulated light flash is superimposed in red over the outdoor scene. 20 consecutive patterns during a part of the 1 ms laser pulse are used to restore the red overlay image. The outdoor scene is also captured at 128x128 resolution (3000 patterns with a subsampling ratio of 18%), when the light source is continuously on, thus visible as a small bright light.

Tests were made to evaluate the number of patterns needed to locate a small light source, in this test only one sensor was used. Instead of using a small window for background reconstruction 500 unique patterns was repeated. The laser was synced in such a way that the laser was active for 500 patterns and then inactive for 500 patterns. Thus we could calculate background reduction for the whole signal and wide range of pattern combinations (different sections

Figure 7: B/W image of the outdoor scene at 128x128 pixel resolution, reconstructed using a subsampling ratio of 18%. The Ø7 cm reflector, seen as a bright dot when the laser is continuously on, is mounted on a tree at 350 m range. The red overlaid image of the simulated 1 ms light flash is reconstructed to 32x32 pixel resolution using 20 consecutive patterns (during a pulse) and illustrates the capability to detect and localize the flash at the same position as the reflector (ground-truth).

of the signal) could be reconstructed to test if the strongest pixel in fact was the light source for each individual image. From the measurements, 500 patterns were analysed and ($M \leq 40$) different consecutive patterns were used to reconstruct a large number of images. The results from the experiments are presented in Figure 8. As can be seen, the probability to locate the flash is almost zero below five patterns but then rises quickly and after 25 patterns reaches almost 100. Because the patterns displayed on the DMD are random, the probability to find the light source is dependent on the specific pattern combinations during the light flash and the SNR.

The same test was conducted both in- and outdoors with variable length to the target, backgrounds and resolutions. The trails showed that the key factor in order to detect and localize the signal was SNR. With higher SNR the probability and number of measurements needed for a successful localization increased respectively lowered.

## 7 CONCLUSIONS

Conventional FPA-based solutions to high speed light flash detection are challenging, due to limitations in frame rates, signal processing demands as well as transmission bandwidth requirements. The sparse na-

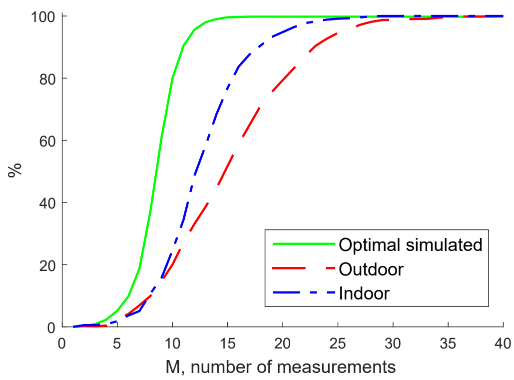


Figure 8: Probability to find the correct pixel (illuminated reflector) in the reconstructed image given $M$ number of samples, using one sensor. Green line shows simulated light flash without noise, blue line from illuminating the reflector indoors in a dark room from ca. 40 m, red line from outdoor trials ca. 350 m.

ture of the transient and highly localized events however suggests that CS-based approaches might be useful. Results of our initial experiments, based on long range detection of 1 ms laser pulses with our DMD-based SWIR SPC, show great potential of both detection and localization of flashes with the high sampling rate provided by the DMD. A high (99%) localization probability have shown to be provided after only 25-30 samples, corresponding roughly to the pulse width of the laser and to 2-3% sampling ratio of a reconstructed image at 32x32 pixel resolution. Although the initial focus has been given to muzzle flash detection, it is also conceivable that the system could be used for sniper optics detection by using active CW or pulsed laser irradiation, using similar techniques as described in the paper. Detection of other transient and spatially limited events of military interest could be explosions and missile launches at longer ranges.

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