Per-Pixel Mirror-Based Acquisition Method for Video Compressive Sensing

Jonathan A. Lima, Cristiano J. Miosso, and Mylène C. Q. Farias
University of Brasilia
Brasilia – DF, CEP: 70910-900, Brazil
Email: jonathanalis@gmail.com

***Abstract*—High speed imaging requires high bandwidth and fast image sensors, what makes it very expensive. With recent developments in the area of compressive sensing and computational photography, new methods are being developed to reconstruct high speed video from low speed cameras using light modulators (global and per-pixel shutters). However, these methods present problems like time dependent measurements and low light efficiency. In this work, we propose a new acquisition method, called the per-pixel mirror-based acquisition method, that uses a new kind of light modulator. Results show that, when compared to methods available in the literature, the proposed method (and its variations) presents better performance in terms of quality and light efficiency.[1]**

***Keywords*-compressive sensing, computational camera, high-speed imaging, video acquisition.**

I. Introduction

High-speed videos allow humans to better visualize fast moving scenes. These videos are very important tools for many applications in science (biology combustion, bio-mechanics, fluid dynamics and others) and industry (equipment design, production, component and material testing) [1]. High-speed videos are generally too fast – not only for the unaided human eye, but also for most low cost commercial cameras that cannot capture videos with temporal resolutions higher than 60 frames per second (FPS). The most common solution for acquiring high-speed videos is to use high-speed video cameras. These cameras have high sensitive sensors capable of acquiring videos with temporal resolutions of thousands of FPS. Unfortunately, they are much more expensive than regular ones [2].

A more recent solution to the problem consists of using compressive sensing theory. In this approach, a high-speed video is reconstructed from a set of linear measurements acquired by common cameras and shutters that scramble the light received by sensors. The most common acquisition methods for high-speed compressive sensing are flutter shutter and per-pixel shutter. Unfortunately, both methods have the same drawback: around 50% of the light is discarded and, consequently, information is lost. Another drawback is that, for both methods, the light coming from different instants of time is integrated into a single pixel causing time dependence. This makes it difficult, at the reconstruction, to separate information from different time instants.

[1]This work relates to a M.Sc. dissertation defended on August of 2014.

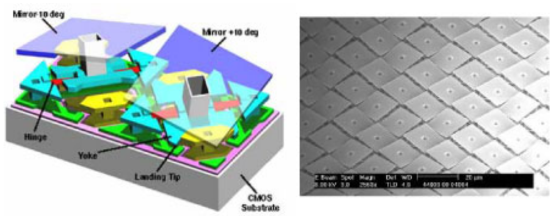
In this work, we propose a new acquisition method for compressive sensing reconstruction of high-speed videos that handles these limitations. The proposed method, named Per-Pixel Mirror-based measuring (PPM), is an acquisition method that uses a set of moving mirrors for redirecting the light into a pixel position. The method does not discard any light (100% light efficient) and it can separate temporal information (time independent measurements). We compare the performances of PPM with the available acquisition methods. We tested the methods for still images, synthetic videos, and natural videos. We simulate the method acquisition process and use the same reconstruction algorithm (TVAL3[3]) for all tests.

The paper is organized as following. Section 2 gives an overview of the compressive sensing theory and of the video compressive sensing acquisition methods available in the literature. Section 3 describes the proposed method, while Section 4 presents the simulation results. Finally, Section 5 presents our conclusions.

II. Acquisition methods for video compressive sensing

Compressive sensing [4], [5] is a method of acquisition and representation of sparse signals at a rate below the Nysquist's rate. Its goal is to reconstruct the signal using an optimization of a sparsity measure and considering the linear measurements restrictions. Recently, compressive sensing has been used for high-speed video reconstruction, what requires that a linear combination of the captured video frames. In this section, we describe two of the most known methods for acquiring measurements using video compressive sensing: Flutter Shutter (FS) and Per-Pixels Shutter (PPS).

1) Flutter Shutter: Flutter shutter (FS) is a method that allows to start and finish sensors exposure several times during a frame interval. This process, which allows a linear measurement acquisition, is implemented in some commercial cameras for high-speed acquisition [6], [7], [8]. In FS, the exposure time is divided into equal time sub-frames (time corresponding to the equal divisions of a frame duration). This way, for all pixels, each sub-frame can be turned on or off. The incoming light corresponding to each sub-frame is integrated at the end of the frame time. Therefore, linear measurements are formed by the information acquired from several sub-frames at different times. Clearly, unless all sub-frames are turned-on, light information is lost. This acquisition mode is used by Holloway *et al.* in their technique Flutter Shutter Video Camera [6] and achieves a 66 % luminous efficiency.



caption(left) DMD and its 2 angles for each mirror. (left) DMD used in the method SPC.

Fig. 1. (left) Close-up of DMD device [9] showing the two possible angles and (left) DMD device used in a single pixel camera (SPC).

2) Per-pixel Shutter: Per-pixel shutter (PPS) is a method of video acquisition that gives a better exposure control, since it makes it possible to turn on or off any of the pixels, several times during the exposure time. One of devices that implements PPS is the Digital Micro-mirror Device (DMD) [10], [11], [12]. DMD is implemented by a set of micro-mirrors that can take two possible angle positions. The first angle directs light to the lens leading to the sensor array, while second angle directs light outwards (i.e. light is thrown away). In Figure 1, an illustration of the DMD device is depicted. DMD is not yet implemented in commercial cameras, being generally used as an external optical system.

There are two different PPS methods. In the first method (PPS1), each pixel is turned on in a single sub-frame. This form of acquisition is used by Hitomi *et al.* for recovering high speed videos technique using a training dictionary [13]. One problem of PPS1 is that the majority of the light is not acquired and, therefore, a lot of information is lost. In the second method (PPS2), pixels can be turned on or off regardless of the sub-frame. At the end of the integration time, each pixel is formed by the sum of the turned-on pixels acquired during the different sub-frames. In other words, each pixel contains information from multiple concurrent sub-frames. However, the implementation of PPS2 generates a loss of about 50 % of the luminous information. Reddy *et al.* uses PPS2 in its programmable pixel compressive camera (P2C2) [14].

III. Per-Pixel Mirror-Based Measuring Acquisition Method

We propose a new method to acquire linear measurements for compressive sensing video reconstruction that does not waste light information: Per-Pixel Mirror-based measuring (PPM). PPM does not integrate the temporal information between different sub-frames into a single sensor. For the implementation of our method, we propose a new device called High-Precision Digital Micro-mirror Device (HPDMD). In order for each micro-mirror to be able to redirect the incoming light to any other pixel, HPDMD must have a higher angular accuracy than DMD. Similarly to DMD, HPDMD can change its angle in a higher speed than FPS.

Let N be the number of pixels of a camera and k the number of sub-frames. In PPM, for each sub-frame, N/k pixels receive light from the current sub-frame. Therefore, for each N/k pixels, k random mirrors are directed to these pixels. In the next sub-frame, other N/k pixels are chosen and k mirrors are redirected to these pixels. At the end of k sub-frames, each pixel will receive light from k mirrors. The proposed method is illustrated in Figure 2. As can be observed from this figure, this process requires that each pixel receives the sum of the light intensity of k random pixels. For PPM, at the end of the integration time of the acquisition process, no light is discarded. This happens because all light is redirected to some pixel. Furthermore, all the light originating from a single sub-frame is directed to a single set of N/k pixels. This means that light from a sub-frame is not mixed with light from another sub-frame, i.e. there is no time dependence between measurements. On the other hand, unlike other forms of acquisition, there is spatial dependence among samples.

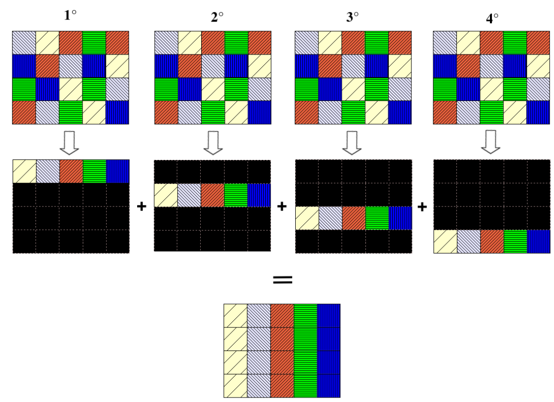


Fig. 2. Proposed method in PPM1 configuration with $N = 80$, $M = 20$, and $k = 4$. For each subframe, only one set of pixels ($M/k = 5$ pixels) receives light. The mirror pattern is the same for all subframes.

There are a number of variations of the PPM configuration. Each pixel of each frame can receive light from up to k mirrors. One possible configuration is to have, for each sub-frame, the same pixel receiving light from the same random mirrors. In other words, the same pattern of mirrors is used for different sub-frames. We call this configuration PPM1, as shown in Figure 2. Another possible configuration consists of choosing different random pixels for each pixel and each different sub-frame. We call this configuration PPM2, as illustrated in Figure 3. Differently from PPM1, each sub-frame has a different mirror random pattern. This configuration is often more interesting than PPM1, because it better satisfies the compressive sensing incoherence property. Table I presents the characteristics of the proposed acquisition method and the methods available in literature, concerning viability, dependence of measurements, and light efficiency .

A. Reconstruction Procedures in the Proposed Method

After acquiring the measurements, the next step is to reconstruct the high-speed video from the acquired linear

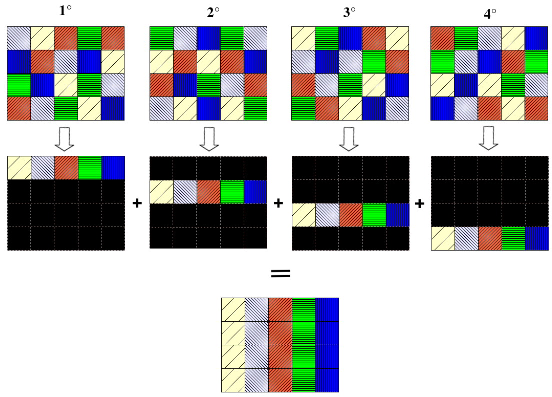


Fig. 3. Proposed method in PPM2 configuration with $N = 80$, e $M = 20$, and $k = 4$. For each subframe, only one set of pixels ($M/k = 5$ pixels) receives light. The mirror pattern is different for all subframes.

TABLE I
CHARACTERISTICS OF ACQUISITION METHODS.

Acquisition Method	**Viability in video cameras**	**Dependency of measurements**	**light information**
Traditional	All cameras	temporal	100%
FS	Some cameras	temporal	50% to 67%
PPS1	Requires DMD	none	$100/k$%
PPS2	Requires DMD	temporal	arround 50%
PPM1	Requires HPDMD	spatial	100%
PPM2	Requires HPDMD	spatial	100%

measurements. The reconstruction algorithm used in this work is based on the minimization of the total variation (TV) using the optimization problem given by the following equation [3], [15]:

$$\hat{s} = \text{argmin}_{s'}(||s'||_{TV}) \text{ such that } y = \Phi\Psi s'. \qquad (1)$$

In this equation, Ψ is the transform basis and Φ is a linear operation corresponding to the acquisition method. For comparison purposes, we tested the acquisition methods described earlier with a fixed reconstruction method. We refer to the TV reconstruction in 2 spatial dimensions as TV2D and to the TV reconstruction in 2 spatial dimensions and 1 temporal dimension as TV3D. TV2D takes advantage of spatial redundancies, while TV3D takes advantage of spatial and temporal redundancies.

IV. Simulation Tests

We test the acquisition methods using 3 sets of signals: (1) still images, (2) synthesized videos, and (3) natural videos. We simulate the acquisition for each method, reconstruct the original signal and, then, compare the SNR of the reconstructed and original signals.

A. Test 1: Natural Images

If the measures of a given video acquisition method is temporally independent, it is possible to reconstruct each subframe separately. The methods that fall into this category are PPS1 and PPM. So, we conducted tests with still images,

TABLE II
SNR OF THE RECONSTRUCED IMAGE FOR EACH METHOD.

SNR	Interpolation	PPS1 and TV2D	PPM and TV2D
64×64	19,3	18,4	22,2
256×256	16,5	16,0	23,2
1024×1024	21,2	21,5	29,3

comparing the results of the acquisition methods after reconstruction with TV2D. For comparison purposes, we also use the interpolation from equally spaced sub-sampling for reconstruction.

We consider a set of gray levels images of size N and a sub-sampling rate of k that leads to N/k samples from each image. This simulates the acquisition of one sub-frame with a exposure time of $1/k$ of the frame time. We consider three image sizes: $k = 4$ and $N = 64 \times 64$, 256×256, and 1024×1024. Figure 4 shows the results for an excerpt of a 1024×1024 image. Table II shows the SNR values for all tests. We can observe that the SNR obtained for interpolation are not much different from what was obtained with PPS1 (by TV2D). The acquisition by PPM shows the best SNR values.

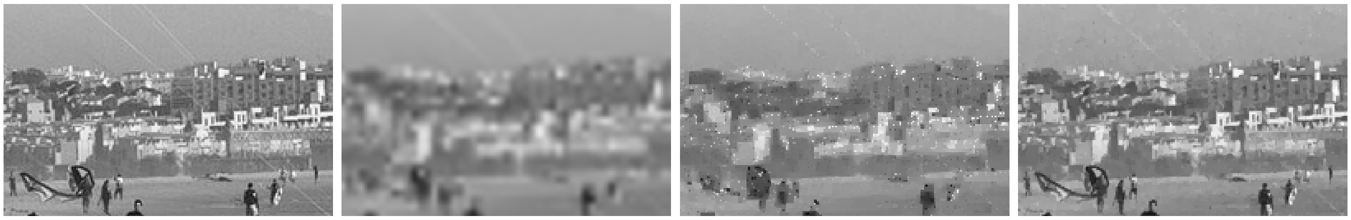
Note that for larger images the performance is better. In fact, the larger the image, the larger is the difference among the SNR results of different acquisition methods. Notice also that the image shown in Figure 4(d) presents better image quality than the images in Figure 4(b) and Figure 4(c), showing that PPM is able to recover even small image details even with only 1/4 of the original measures.

These initial tests show the potential of using the proposed methods to acquire high temporal resolution videos. If we divide the original frames of a camera by 4 and take linear measurements of each sub-frame, we can recover four images with a good quality. Therefore, we can increase the temporal resolution 4 times, maintaining a number of pixels. We achieve this with no temporal redundancy among sub-frames, that is the four sub-frames can be completely different from each other. Furthermore, we observe the potential for super-resolution applications. Measures can be taken with cameras with $1/4$ of the final resolution.

B. Test 2: Synthetic Videos

In this section, we use a set of synthetic videos that simulate the general aspects of a natural video, like movement, occlusion, deformation, and light change. We use ellipses (phantoms) and rectangles as scenes objects. They were chosen because they are widely used in compressive sensing for medical image reconstruction. Figure 5 (a) shows a sample video frame taken from a synthetic video.

For the five acquisition methods, we use synthetic videos of sizes $100 \times 100 \times 128$, $100 \times 100 \times 256$, $200 \times 200 \times 128$, and $200 \times 200 \times 256$. We test the methods with 50%, 25%, 12.5%, and 6.25% sub-sampling rates. For all methods and sub-sampling rates, reconstruction is performed with TV3D minimization. Simulation results are presented in Table III.



(a) Original (b) Interpolated, SNR=21,16 (c) PPS1,SNR=21,50 (d) PPM,SNR=29,25

Fig. 4. Reconstruction results for an excerpt of a 1024×1024 image. (a) Original image. (b) Equally spaced sub-sampled and reconstructed by interpolation, SNR=21.4. (c) PPS1 and TV2D reconstruction, SNR=21,5. (d) PPM and TV2D reconstruction, SNR=29,3.

TABLE III
AVERAGE SNR (dB) OF RECONSTRUCTED SYNTETIC VIDEOS FOR EACH TESTED ACQUISITION METHOD, USING TV3D RECONSTRUCTION.

Video size	Acquisition method	Sub-sampling rate $k=2$	$k=4$	$k=8$	$k=16$
	FS	42.9	6.3	2.4	1.7
100×	PPS1	9.2	3.0	-0.3	-1.7
100×	PPS2	9.3	11.1	6.7	5.3
128	PPM1	27.2	20.1	12.2	1.2
	PPM2	67.2	55.6	33.7	8.7
	FS	42.4	8.5	1.2	0.74
100×	PPS1	9.2	2.7	-0.3	-1.7
100×	PPS2	9.3	11.6	7.0	5.3
256	PPM1	31.2	18.6	11.5	1.9
	PPM2	76.8	55.7	32.9	8.8
	FS	49.5	9.0	4.9	4.8
200×	PPS1	11.8	12.0	0.8	-1.4
200×	PPS2	11.7	13.8	10.4	8.4
128	PPM1	33.7	27.4	24.9	8.2
	PPM2	71.3	55.2	44.3	22.6
	FS	36.8	9.0	6.8	1.9
200×	PPS1	11.8	12.0	0.8	-1.4
200×	PPS2	11.7	14.1	10.4	8.5
256	PPM1	48.3	33.2	25.9	6.4
	PPM2	73.1	58.8	44.9	25.6

Note that, in most cases, the reconstruction using PPM (both PPM1 and PPM2) shows the best performance. When compared to PPS2 (the best PPS method), PPM1 and PPM2 show gains of up to two dozens dB. Furthermore, when we fix the spatial resolution and vary the number of frames, results do not change much. However, when we increase the spatial resolution and fix the number of frames, SNR values increase considerably. This happens for all acquisition methods and all sub-sampling rates, being more evident for the proposed method and for higher sub-sampling rates. So, video spatial resolution seems to be more important for reconstruction quality than the total number of pixels in the video.

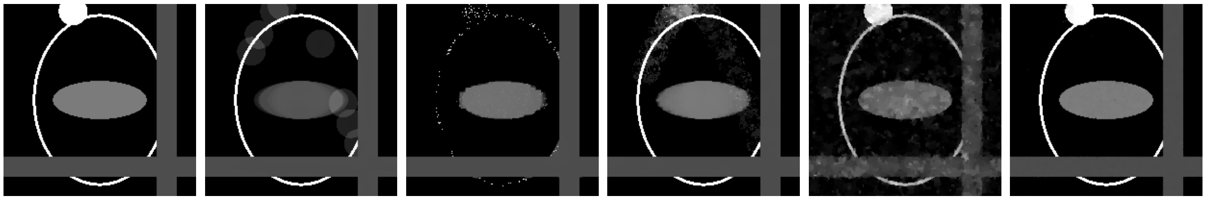
Figure 5 shows an illustration of the results obtained using the 5 acquisition methods with a sub-sampling factor of 16x. This example corresponds to the sub-frame 85 of the $200 \times 200 \times 128$ synthetic video. Figure 5(a) shows the original sub-frame. This is the fifth frame of a set of 16 frames that were reconstructed together (frames 81 to 96). In this set of frames, the white circle (shown in the top of image) moves to the top region of the image, hits the edge and, then, moves to the bottom right region. This particular frame (the 85th) shows the moment when the white circle is at the top edge of the image.

The reconstruction using FS, illustrated in Figure 5(b), clearly shows interference of adjacent frames and, therefore, presents a lower SNR. The reconstruction using PPS1 (see Figure 5(c)) does not show any traces of previous or subsequent frames, given that this method does not have temporal dependencies among measurements of different sub-frames. However, much information of the original frame is missing because the amount of acquired light is too low for an accurate scene reconstruction. The reconstruction using PPS2, illustrated in Figure 5(d), also shows traces of previous sub-frames. This shows that time dependence among measures may influence the reconstruction, especially for areas where there is movement. We observe that the higher the sub-sampling factor, the greater this dependence is and, therefore, the more traces of previous frames are present in the reconstructed frame.

In PPM, these two problems are addressed simultaneously. Figures 5(e) and 5(e) show frame pictures reconstructed using PPM1 and PPM2, respectively. We observe that there are no traces of the adjacent sub-frames in the reconstructed frame. In addition, the images acquired with these methods have more details than the ones obtained with PPS1 because 100% of original light is preserved. The quality of the reconstruction using PPM2 (see Figure 5(f)) is also better than what was obtained using PPM1 (see Figure 5(e)), showing that the use of a random pattern of mirrors for each sub-frame leads to better results. Overall, we see that methods with temporal independence among measurements are able to better separate temporal information originating from different sub-frames.

C. Test 3: Natural Videos

Results obtained with synthetic videos provided good directions on which parameters can lead to best results. High spatial resolutions lead to better reconstruction quality and, apparently, the number of frames of the video does not significantly affect the quality of the reconstruction. Nevertheless, the phantoms shown in the previous sections are very sparse with respect to the finite difference domain, which is measured by the TV operator. As a consequence, TV minimization results are, in general, good. Unfortunately, natural videos are not as sparse.



(a) Frame 85 (b) FS (c) PPS1 (d) PPS2 (e) PPM1 (f) PPM2

Fig. 5. Test for methods FS, PPS1, PPS2, PPM1, and PPM2 for a sub-sampling rate of 16x of a 200×200 ×128 synthetic video.

Considering this, we chose to test the acquisition methods using a set of high definition (HD) videos. Since the spatial resolution has a greater impact on the reconstruction quality than the number of frames, for the simulation tests we chose a set of only 16 frames of each original video. In other words, we decided to minimize the number of frames in order to be able to increase the spatial resolution of the video without dramatically increasing the amount of data that needs to be stored in memory. Since the number of frames depends on the sub-sampling rate, to test the sub-sampling rate of 16x, we need a minimum of 16 frames of the original videos. Thus, each sampling method generates samples corresponding to 1 frame, which is the number of samples that are captured by the camera sensors at a time.

The original HD videos were obtained from The Consumer Digital Video Library (CDVL). The videos are uncompressed (.avi format) with resolution 720×1280, captured at 50 FPS and 4:2:0 color sampling. For these videos, we choose 1 set of 16 frames and converted them to gray intensity levels. The videos have a high quality, with no visible degradations. In the tests performed with phantoms, for the highest sub-sampling rates, best results were obtained using PPS2 and PPM2 methods. Since the tests on HD content require a considerable amount of time and disk space, we choose not re-test the FS, PPS1, and PPM1 methods.

As our method allows frame by frame reconstruction (the method is time independent), we added a variation of the method for testing purposes. With the same measurements of PPM2, we perform the TV2D reconstruction of each frame separately. We take the first M/16 samples and reconstruct the first frame. Then, we take the next M/16 set of samples and reconstruct the second frame. We keep doing this until the last frame. We call this configuration PPM-2D. Notice that PPS2 does not allow this configuration because samples from different sub-frames are not separated. We tested other variation of PPM that consists of taking the video generated by PPM-2D and reconstructing it again with TV3D. We call this configuration PPM3.

Figure 6(a) shows a 600×600 stretch of the first frame of video 9. In this frame, notice that there is a shadow that covers the man's back. This shadow moves during the video. Figures 6(b), (c), (d) and (e) show the reconstructions using PPS2, PPM2, PPM-2D and PPM3, respectively, with a sub-sampling rate of 16x. For the video frame reconstructed with PPS2, although the back of the man should not be visible, it appears in the reconstructed frame. Therefore, as a consequence of temporal dependence, PPS2 is not able to separate the content of neighboring frames. PPM2 generates a noisy reconstruction. Both PPM-2D and PPM3 got much better results, with PPM-2D showing slightly better SNR values than PPM3. On the other hand, visually, PPM3 results are a little better, showing less of the characteristic TV minimization artifacts.

TABLE IV
AVERAGE SNR (DB) FROM NATURAL RECONSTRUCTED VIDEOS(AVERAGE FOR ALL 12 VIDEOS).

k=	PPS2	PPM2	PPM-2D	PPM3
4	14.0	16.8	23.5	22.3
8	12.5	11.4	20.3	19.4
16	10.3	9.0	17.9	17.3

SNR reconstruction results for PPS2, PPM2, PPM-2D, and PPM3, using sub-sampling rates of 4, 8, and 16, are shown in Table IV. The last line of this table shows the average results for all videos. Comparing PPS2 and PPM2, we observe that PPM2 presents better results for the sub-sampling rate of 4: an average SNR of 14dB for PPS2 versus 16, 8dB for PPM2. But, for higher sub-sampling rates, PPS2 performs better than PPM2 in most cases. However, both results are considerably worst than what was obtained for PPM3 and PPM-2D, both in terms of SNR and in terms of subjective quality. Images reconstructed with PPM3 and PPM-2D have more defined edges (more details) and much less noise. Particularly, with PPM-2D, each frame is reconstructed alone and, therefore, there is no mixture among the frames. This suggests that temporal activity favors our methods.

D. *Final remarks based on empirical results*

We performed a set of simulations using the proposed acquisition methods and methods available in literature. For videos with only one frame (still images), results show that the proposed method PPM has better performance (SNR between 5 and 8 dB) than other tested method (PPS1). For higher spatial resolutions, the results got even better, showing a high quality for sub-sampling rates of 4x. For synthetic video, PPM2 presents the best results in terms of reconstruction quality, showing higher SNR values when compared to other methods. In fact, the reconstructed signals for this type of video are hard to distinguish from the original signals (even for a 16x sub-sampling rate). This shows that the proposed

(a) original (b) PPS2 (c) PPM2 (d) PPM-2D (e) PPM3

Fig. 6. Results for methods PPS2, PPM2, PPM-2D e PPM3 for video 9, with a 16x sub-sampling rate.

method is promising. However, for natural HD videos we do not have the same sparsity. In the tests, PPM2 performs worse than PPS2 in most cases. But, when the scene had more movement PPM2 performs better. We also tested a frame by frame reconstruction method that uses the same measurements of PPM2 (PPM-2D) and reconstructing it again with TV3D using PPM-2D as initial solution (PPM3). PPM3 shows much better results than PPM2 and PPS2, with improvements of around 70 %.

V. Conclusions and Future Works

We proposed a new video acquisition method for high-speed reconstruction. The proposed method, PPM, spatially mixes the light using micro-mirrors in a way that no light is discarded. For time independence, the light is separated for each sub-frame. Up to our knowledge, no method in the literature can ensure both time independence and light efficiency. We tested the method on still images, synthetic videos, and natural videos, comparing the proposed methods with other methods available in the literature. For images and synthetic videos, the proposed method performed much better than the other methods. For natural videos, changing the reconstruction method, we were able to obtain very good results.

The main limitation of the proposed method is that the device needed to implement the acquisition is not yet commercially available. Also, although the proposed method has time independence, but it does not have spatial independence. Therefore, the results are worse for the videos with great amount of noise. Future works include implementing other variations of PPM, implementing hybrid methods (e.g. merging PPS2 with PPM), exploring applications in super-resolution, testing other types of reconstruction, and implementing the HPDMD device in hardware.

Partial results of this work were published in the 2014 European Signal Processing Conference (EUSIPCO) with the title "Per-Pixel Mirror-Based Acquisition Method for Video Compressive Sensing". A journal paper with the complete work is currently being finalized.

Acknowledgment

This work was supported in part by the University of Brasília and in part by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES).

References

[1] "About high-speed digital video cameras," http://www.fastecimaging.com/support/resources/about-hsv, acessed in December, 2014.

[2] Photron, "Photron," http://www.photron.com/, acessado em Março, 2013.

[3] C. Li, W. Yin, and Y. Zhang, "User's guide for tval3: Tv minimization by augmented lagrangian and alternating direction algorithms," *CAAM Report*, 2009.

[4] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," *Information Theory, IEEE Transactions on*, vol. 52, no. 2, pp. 489–509, 2006.

[5] D. L. Donoho, "Compressed sensing," *Information Theory, IEEE Transactions on*, vol. 52, no. 4, pp. 1289–1306, 2006.

[6] J. Holloway, A. Sankaranarayanan, A. Veeraraghavan, and S. Tambe, "Flutter shutter video camera for compressive sensing of videos," in *Computational Photography (ICCP), 2012 IEEE International Conference on*. IEEE, 2012, pp. 1–9.

[7] A. Agrawal, M. Gupta, A. Veeraraghavan, and S. G. Narasimhan, "Optimal coded sampling for temporal super-resolution," in *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*. IEEE, 2010, pp. 599–606.

[8] A. Veeraraghavan, D. Reddy, and R. Raskar, "Coded strobing photography: Compressive sensing of high speed periodic videos," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 33, no. 4, pp. 671–686, 2011.

[9] Nokia, "Snls 2200 light activation system," http://www.supernovalifescience.com/proddetail.php?prod=9000, acessado em Março, 2015.

[10] M. Douglass, "Dmd reliability: a mems success story," in *Micromachining and Microfabrication*. International Society for Optics and Photonics, 2003, pp. 1–11.

[11] S. K. Nayar, V. Branzoi, and T. E. Boult, "Programmable imaging: Towards a flexible camera," *International Journal of Computer Vision*, vol. 70, no. 1, pp. 7–22, 2006.

[12] G. Bub, M. Tecza, M. Helmes, P. Lee, and P. Kohl, "Temporal pixel multiplexing for simultaneous high-speed, high-resolution imaging," *Nature methods*, vol. 7, no. 3, pp. 209–211, 2010.

[13] Y. Hitomi, J. Gu, M. Gupta, T. Mitsunaga, and S. K. Nayar, "Video from a single coded exposure photograph using a learned over-complete dictionary," in *Computer Vision (ICCV), 2011 IEEE International Conference on*. IEEE, 2011, pp. 287–294.

[14] D. Reddy, A. Veeraraghavan, and R. Chellappa, "P2c2: Programmable pixel compressive camera for high speed imaging," in *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*. IEEE, 2011, pp. 329–336.

[15] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D: Nonlinear Phenomena*, vol. 60, no. 1, pp. 259–268, 1992.