Compressive Image Sensor Architecture with On-Chip Measurement Matrix Generation

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***Abstract*— A CMOS image sensor architecture that uses a cellular automaton for the pseudo-random compressive sampling matrix generation is presented. The image sensor employs in-pixel pulse-frequency modulation and column wise pulse counters to produce compressed samples. A common problem of compressive sampling applied to image sensors is that the size of a full-frame compressive strategy is too large to be stored in an on-chip memory. Since this matrix has to be transmitted to or from the reconstruction system its size would also prevent practical applications. A full-frame compressive strategy generated using a 1-D cellular automaton showing a class III behavior neither needs a storage memory nor needs to be continuously transmitted. In-pixel pulse frequency modulation and up-down counters allow the generation of differential compressed samples directly in the digital domain where it is easier to improve the required dynamic range. These solutions combined together improve the accuracy of the compressed samples thus improving the performance of any generic reconstruction algorithm.**

Keywords—compressive sampling; cellular automaton; pulse-frequency modulation;

I. INTRODUCTION

Compressive Sampling is a signal processing framework in which sparsity is exploited in order to reduce the number of necessary samples to reconstruct the original signal. This property can either exist in the sampling domain of the signal or with respect to other basis i.e. Fourier, wavelets or curvelets [1]. If the original signal can be sparsely represented in some domain, like natural images [2], then it is possible to recover it from a much smaller number of samples than that indicated by Nyquist-Shannon theorem. To recover a compressively sampled signal it is necessary to solve this inverse linear equation:

$$Y = \Phi\Psi\alpha \quad (1)$$

Being Y the set of compressed samples derived from the original signal, Φ the compressive strategy, Ψ the sparsifying dictionary and α the coefficients of the original signal represented in an opportune basis. The compressive strategy Φ represents the methodology through which compressed samples Y are taken; each compressed sample is a linear combination of the elements that constitute the original signal The sparsifying dictionary Ψ is a matrix that multiplied by a discrete signal returns a vector containing the coefficients α of the transformation of the original signal to a domain in which its representation is sparse. The amount of compressed samples Y is typically lower than the amount of elements contained in α. Although underdetermined problems are considered ill-posed, compressive sensing can lead to a unique solution by the means of convex optimization. The condition for this to be achieved is that the product of Φ and Ψ holds the restricted isometry property (RIP) [3].

There are two set of methods that are followed nowadays to build a compressive strategy within an image sensor, the first one is to pick each element of Φ from a random distribution and the second is to use an incoherent orthobasis matrix. Each one of these two methods yields different kinds of solutions for its physical implementation. Up until now, incoherent orthobasis have been implemented only into optic elements of image sensors 0 while on the other hand random distributions techniques are more popular and have been implemented both using optic elements [5] and dedicated circuitry [6]. Random distribution techniques applied to image sensing rely on the use of a sub-Gaussian distribution. In this distribution each element of the strategy is picked at random to be either one or zero. This choice simplifies the problem at hand because each compressed sample will simply be the sum of the readings of a subset of the pixels that form the sensor. Independently of the solution chosen to introduce the compressive strategy, there are two major limitations that arise. To be able to recover a signal from compressed samples, a reconstruction algorithm needs to know the compressive strategy i.e. the matrix with which each compressed sample has been generated. For that to happen it either means that the compressive strategy is being generated and transmitted between the sensor and the system in charge of reconstruction or that it must be stored in a memory in both places. The second problem is that of dynamic range: compressed samples are linear combinations of the outputs of the pixels forming the sensor; as such, when a sub-Gaussian distribution of ones and zeros is chosen, the number of bits needed to describe this combination is significantly higher than the amount of bits needed to describe the value of each individual pixel. This problem increases as $\log_2 N$ being N the number of pixels used to create a compressed sample. A common workaround to offset these limitations is the use of block-based compressive sampling [7]. This technique is used to separate the pixels of the image sensor into sub-sets. To each

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sub-set is applied the same compressive strategy smaller in size than the full pixels grid. There are several examples of implementation present in literature [8][9][10] and, while all of these solutions allow for the generation compressed samples efficiently, the result of reconstruction using block-based compressive sampling is suboptimal. Reducing the size of the image to which compressive sampling is applied also reduces the sparsity of the image itself. This leads to an increment of the number of compressed samples needed for maintaining the reconstruction error under a certain tolerance. Moreover, these solutions, even though to a lesser extent, are still affected by errors that may occur due to inadequate resolution of the collected samples.

We propose a new architecture for the generation of a full-frame compressive strategy that does not need transmission or storage as well as a way to digitize the compressed samples that vastly improves their dynamic range. To achieve this result we implement a cellular automaton (CA) following rule 30 [11] around the pixel grid for the pseudo-random selection of pixels. This solution allows us to generate the compressive strategy on-chip without transmitting or saving it on an external memory, because the pseudo-random sequence can be reproduced at both ends of the system from the initial seed. Inside the array we perform a pulse-frequency modulation of the pixels values and we aggregate these outputs using up-down counters for each column of the pixel grid.

II. On-Chip Compressive Strategy Generation

The creation of a full-frame mask using pseudo-random patterns only needs an initial seed to retrieve the full pseudo-random sequence forming the compressive strategy without the need of storing it in any memory. Pseudo-random patterns can be generated using different methods. Notable examples in compressive sampling are Hadamard vectors [12] or linear feedback shift registers [13]. We propose to implements a cellular automaton (CA) for this purpose. A 1-D CA is made of a row of cells [11] presents two key advantages over the previous methods. First its architecture is easily implementable in CMOS technology and second, since the evolution of each cell depends on its own current state and those of its closest neighbors (Fig. 1 C L R inputs), it is readily scalable to fit any size of pixel array. A binary CA with radius-1 neighborhood, has 256 possible truth tables, each one usually termed as a rule. Rule 30 makes the CA display an aperiodic (class III) behavior, which will be our pseudo-random sequence. For the implementation of the compressive strategy we place cells implementing rule 30 Fig. 1 around the pixels grid, one for each column and row. The output of each cell is used as a selection signal for the rows and columns of the pixel grid.

III. Pixel Architecture Logic

To form a compressed sample, the pixel value is pulse-frequency modulated and sent to one of two column buses that gather the pulses coming from all the pixels belonging to the same column Fig. 2. The selection signals generated by the cells of the CA along with the in-pixel logic (XOR) will determine to which bus the pixels output will go and activate

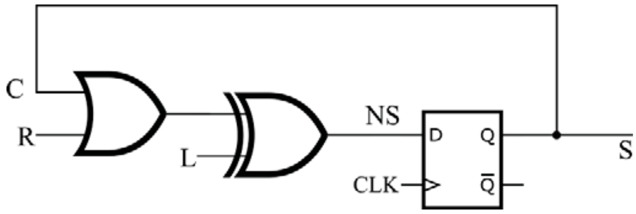

Fig. 1. Implementation of a Rule 30 cell of a cellular automaton

the corresponding switch Fig. 3. Since a XOR between two logical inputs has four possible outcomes which are equal in pairs, the pixel output has the same a priori probability to be sent to each of the two lines. These buses are then used as inputs of an up-down counter that accumulates the contributions of the column. Then a cascade of adders generates the already digitized compressed samples.

During integration time a pulse train is created so that the frequency, f , of the pulses varies in accordance with the instantaneous of the photocurrent at given sampling intervals. The amplitude and width of said pulses on the other hand is kept constant. In this case the modulating signal is the photocurrent intensity flowing through the illuminated photodiode, I_{ph}:

$$f = \frac{I_{ph}}{C(V_{rst}-V_{ref})} \tag{2}$$

Being V_{rst} the reset voltage of the pixel, C the capacitance of the photodiode and V_{ref} the reference voltage of the operational amplifier used to generate the pulse train. The use of a varying voltage reference allows us to adapt the frequency of the pulse train for a particular light intensity and avoid saturation of the counters used to collect the compressed samples.

By using PFM at pixel level and then counting the pulses at column level we are conveying the problem of the dynamic range of the aggregated signal to the digital domain where it can be increased just incorporating additional resources. Additionally, by taking into account the saturation of the counters bad samples can be discriminated, avoiding reconstruction artefacts.

IV. Compressed Samples Extraction

Another problem that arises using a compressive sensing strategy based on full-frame pseudo-random distributions which elements can be either one or zero is that each compressed sample has the potential to have a much larger value than that of a single pixel. If we were to describe each compressed sample using the same grain employed for the pixels, the digital values of the compressed samples would require several bits more than the 8b or 12b normally used to digitize the content of a single pixel. To resolve this problem we devised a solution divided into two steps. First we have introduced A/D conversion by means of in-pixel PFM and per column pulse counting, thus moving the problem of dynamic range to the digital domain where it is more easily treated. Second, the common lines of each column of the pixel grid will

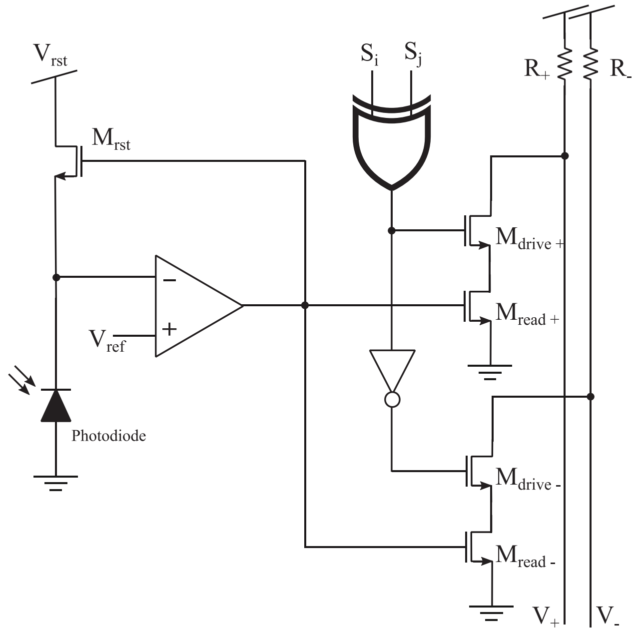

Fig. 2 Pixel Schematic

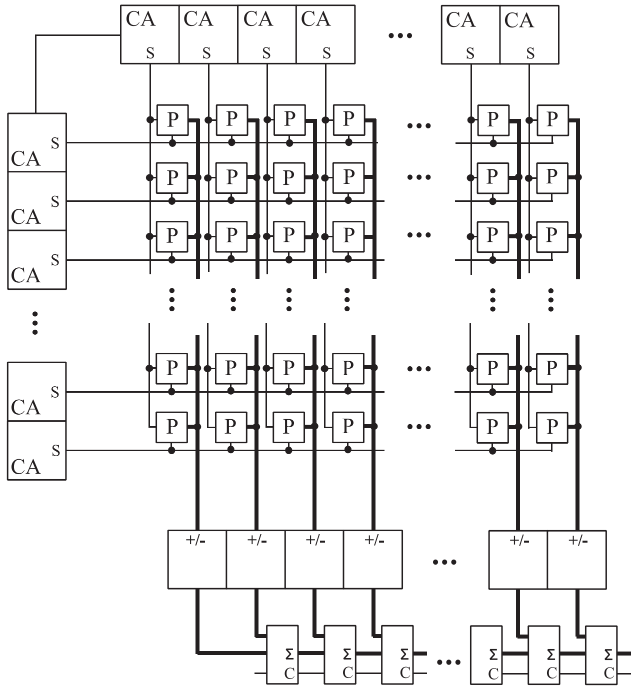

Fig. 3 Sensor Architecture

be both used as inputs for up-down counters, Fig. 3.Every counter will aggregate the contributions coming from some pixels as positives and the rest as negatives depending on the combination of the row and column selection signals. In this way we will collect differential measurement greatly decreasing the average size of the compressed samples. During reconstruction it will be equivalent to using a compressive strategy which coefficients can be either ones or minus ones. Each column counter will generate part of the compressed sample. Summing all of them together will deliver a single compressed sample. This is an important aspect of the architecture that we propose since the solutions presented in the literature until now are not able to generate compressed samples with the same resolution of the original pixels, thus worsening the reconstruction process.

V. Functional Verification

To prove the functionality of our architecture and the performance of reconstruction algorithms using the extracted compressed samples we have simulated a model of the proposed architecture using MATLAB. The blue bars in Fig. 4. represent a study of the average root mean square error (RMSE) of reconstruction for 10 64×64 pixels images[1] over a varying number of compressed samples reconstructed using NESTA convex optimization algorithm [14]. We compare the results achieved with the RMSE of reconstruction of those same images compressed performing a block based compressive sampling strategy (red bars). We devised the block based strategy by dividing each image in 64 sub-images of 8×8 pixels to be treated separately. As we can see applying a full frame compressive strategy delivers better reconstruction errors. Moreover, the higher is the compression ration the better is the result of the full frame strategy compared to the block based one. This fact strengthens our statement that trying to use block-based compressive sampling to separate portions of a big image in order to sample them independently deteriorates the quality of the process. It also proves that trying to obtain a full-frame compressive strategy improves reconstruction and diminishes the amount of samples that the sensor needs to generate in order to maintain a certain level of tolerance during reconstruction. Another test that we have performed aim to study the resources needed to recover the images in terms of time invested into the reconstruction process. The blue bars in Fig. 5.represent the average time of reconstruction over the number of samples used for the full frame compressive strategy. Once again we compared it with the amount of time consumed for the recovery of those images from a block based sampling strategy (red bars). We can see that the resources needed to retrieve the images on lower compression ratios favour the block based sampling strategy. However, as we diminish the amount of samples, the time of reconstruction reverses its tendency allowing the full frame compressive strategy to outperform its block based counterpart both in RMSE and time.

VI. Conclusions

We have introduced a new architecture able to collect compressed samples using pseudo-random distributions generated on-chip. The pattern generated by the cellular automaton does not need to be transmitted and can be easily recovered by simply knowing the initial seed. We also avoid splitting the sensor array in smaller portions worsening the

[1] These images can be found at: http://www2.imse-cnm.csic.es/icaveats/64x64px_images/

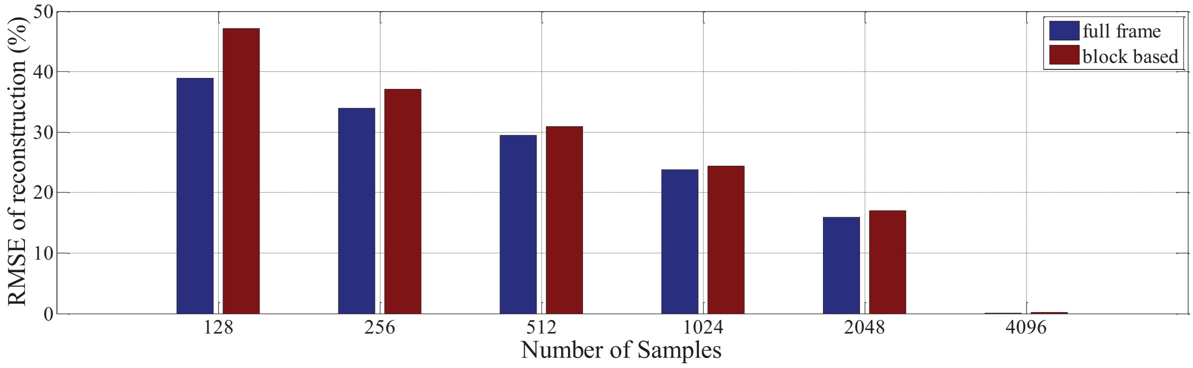

Fig. 4: average RMSE of reconstruction obtained using a full frame compression strategy and a block based compression strategy

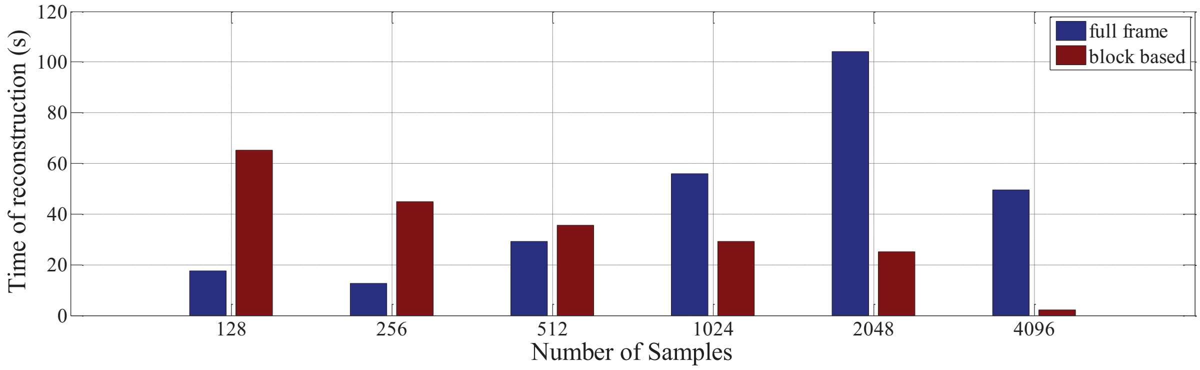

Fig. 5: (a) average time of reconstruction obtained using a full frame compression strategy and a block based compression strategy.

quality of the samples or introducing asymmetries in the design of the sensor array. The solution applied to digitize the compressed samples improves their dynamic range and gives the possibility of discarding saturated samples thus optimizing reconstruction. These features, at best of our knowledge are introduced in this article for the first time

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