On the Design of Change-driven Data-flow Algorithms and Architectures for High-speed Motion Analysis

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Abstract: Motion analysis is a computationally demanding task due to the large amount of data involved as well as the complexity of the implicated algorithms. In this position paper we present some ideas about data-flow architectures for processing visual information. Selective Change Driven (SCD) is based on a CMOS sensor which delivers, ordered by the absolute magnitude of its change, only the pixels that have changed after the last time they were read-out. As a natural step, a processing architecture based on processing pixels in a data-flow method, instead of processing complete frames, is presented. A data-flow FPGA-based architecture is appointed in developing such concepts.

1 INTRODUCTION

Motion analysis is an important issue in the field of computer vision, being the involved algorithms commonly based on the analysis of a sequence of still images. This implies that most of the times there is a large amount of data and the algorithms involved are complex and time consuming. Researches have focused their efforts onto improving the well-known technology for acquiring images, or the computing systems. Nevertheless, little effort has been put into more innovative acquisition or computing approaches to reduce this amount of calculus.

There are several different approaches for motion analysis. From amongst them differential methods are a type of motion analysis algorithm that typically involves full image processing, where each image is a snapshot taken at fixed intervals. Typically, the normal procedure implies the application of several preprocessing filters on the entire image and for each image in the sequence. Next, some more complex processing stages are applied. Whether there have been many changes in the image, only a few, or even no changes at all. The sequence of instructions is systematically applied to the entire image. No matter if there is any new relevant information, being a waste of time and energy.

Visual systems of living beings can offer smarter solutions in the topic of image processing. The visual system of most biological systems does not capture images and send them sequentially to the brain at a fixed rate. The idea of a sequence of still snapshots is not present in biological systems. Most biological vision systems are based on different types of photoreceptors that react to the light intensity delivering its information asynchronously to higher levels of the cognitive system (Gollisch and Meister, 2010).

A Selective Change Driven (SCD) camera delivers only the pixels that have changed since the last read-out. A SCD sensor delivers only non-redundant information, that is, information that has changed. Moreover, pixel delivery is ordered by the absolute magnitude of its change. Therefore, if there are time constraints, the most significant changes in the images will be processed, discarding minor variations. Following this argumentation, it is possible to implement a data-flow policy in the algorithm execution with a conventional CPU, processing only those pixels that have changed. A pixel only triggers the instructions that depend on it. Moreover, it is possible to implement a custom data-flow architecture for processing only changing information. This strategy will decrease the total amount of data to be processed, speeding-up the algorithm execution.

In the literature there have been other approaches which go beyond the limitations of frame-grabber vision systems. In (Mahowald, 1992) it is proposed the first silicon retina following Address-Event Representation (AER) principles. Following this work, many others have taken up the idea of replacing frame

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capturing, transmission and processing with single pixel information (Higgins and Koch, 2000) (Chi et al., 2007) (Lichtsteiner et al., 2008) (Camunas-Mesa et al., 2010).

2 SCD SYSTEM AND PROCESSING

A SCD system has as a main element a SCD camera, and with this purpose, a new visual sensor which implements the SCD behavior has been developed. The sensor, built in CMOS technology, has a resolution of 32x32 pixels and, although we assume this resolution is low for many applications, it is sufficient for demonstration purposes and can even be useful in some cases.

In the SCD sensor every pixel works independently of the others. A capacitor is charged, simultaneously for each pixel, to a voltage during an integration time. Every pixel has an analogue memory with the last read-out value. The absolute difference between the current and the stored value is compared for all pixels in the sensor; the pixel that differs most is selected using a Winner-Take-All circuit (WTA) (Zuccarello et al., 2010) and its illumination level and coordinates are read out for processing. It is important to note that the concept of snapshot at instant t can be kept, taking into account that all the photodiode charges begin and finish at the same time. The subsequent read-out order is performed by the WTA circuit. All the sensor control signals are generated with a 32-bit PIC microcontroller running at 80 MHz which is connected to a computer through a USB link. Further details about this new sensor, the camera and its use in limited-resources systems can be found in (Pardo et al., 2011).

2.1 SCD Algorithms

The design of image processing algorithms within the SCD formalism requires a change in the way of thinking about how the programming instructions are applied to data. A more detailed explanation of how to develop SCD algorithms can be found in (Boluda et al., 2011).

A generic motion analysis algorithm can, many times, be modeled as a pipeline of successive different transformations to the image flow: filtering, feature extraction, etc. Between these processing stages intermediate values are stored. Most of them can be understood as intermediate images, but others can not be viewable in a straight forward way, these images being called intermediate images. Thus, each stage of the image processing pipeline (except the first which has as input the initial pixel flow) has as input full intermediate images and also produces full intermediate images as output. No matter whether or not the initial pixels or intermediates results have changed. All the instructions at each stage are inevitably applied to the data, even if they do not generate any change.

The SCD execution flow is related with data-flow architectures: each new pixel fires all the instructions related with this new data. If there are no data changes no instructions are fired (and neither time nor energy is consumed). Initially the SCD camera delivers those pixels that have changed (gray level and coordinates). Then the first stage updates the contribution of this new pixel value to its output intermediate images. Following this idea all the stages do the same. When new input data arrives at any intermediate stage, then all the related instructions are fired, updating the output intermediate images.

The SCD sensor, as already mentioned, allows a special way of ńon-accuratefunctioning. As the pixels are read-out by the magnitude of their change, it could be possible not to process all the changing pixels, but only the first received pixels, which are those that offer a greater variation. This behavior could be desirable if there were computational time restrictions and less accurate algorithm results could be acceptable. Some experiments were been performed following these ideas, simulating a SCD camera and applying this strategy to differential algorithms.

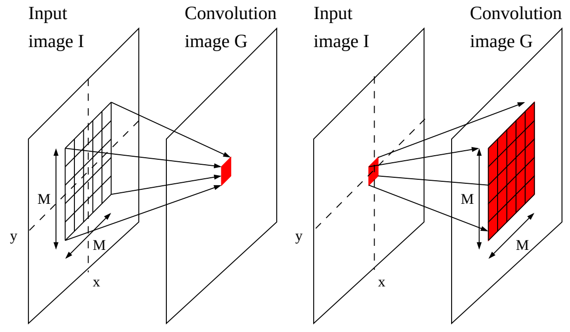
2.1.1 Linear Spatial Operators

Linear spatial operators are very common transformations used for preprocessing or feature extraction. Spatial operators can be expressed as the systematic application of a convolution mask to all the pixels of the image. Let's say that G is the result image of applying the $M \times M$ convolution mask $w_{i,j}$ to the image I taken at instant t, then each $G_{x,y}$ pixel can be calculated as:

$$G_{x,y} = \sum_{i=\frac{1-M}{2}}^{\frac{M-1}{2}} \sum_{j=\frac{1-M}{2}}^{\frac{M-1}{2}} w_{i,j} I_{x+i,y+j} \tag{1}$$

where $I_{x,y}$ is a pixel of the image I.

With a SCD sensor, the way of computing the filtered image G is different. There will be a set of n' changing pixels that have been taken at the same time, not a full input image. The G image must be changed only with the contribution of the n' pixels. An individual $I_{x,y}$ pixel taken at instant $t+1$ contributes to $M \times M$ pixels of G, thus this input must be updated adding the new value and removing the old one. Figure 1 shows



(a) Classical spatial filtering (b) SCD spatial filtering

Figure 1: Pixels involved in the computation of linear spatial filtering.

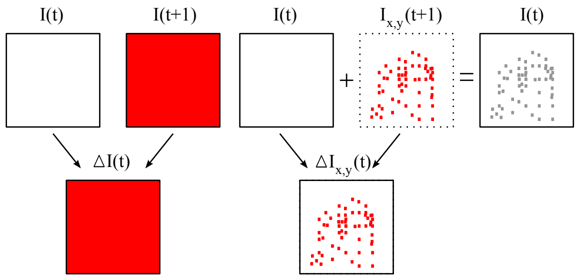


Figure 2: Comparison between the classical implementation of the differential operator and the SCD implementation.

an example of the application differences of a convolution mask in the classical way (a) and the SCD method (b). It seems that there is a growing number of operations, but it must be noted that the number of operations remains constant if all the pixels have changed. As this scenario is the worst case, in general there will be much less operations. In general, when the SCD camera delivers the pixel $I_{x,y}$ in the instant $t+1$ the modified pixels in the G image are:

$$G_{x+i,y+j} = G_{x+i,y+j} + w_{-i,-j}(I_{x,y}(t+1) - I_{x,y}(t)) \quad (2)$$

$$\forall\, i,j \in \left[\tfrac{1-M}{2}, \tfrac{M-1}{2}\right]$$

The difference between the new $I_{x,y}(t+1)$ and the old value $I_{x,y}(t)$ is performed as a first operation. Afterwards, there are updated M^2 pixels of G.

It is possible to see how changing pixels trigger the instructions that have a dependency with them. This is the way SCD processing works. Only the needed operations will be executed and no redundant computations will be performed. In the case of spatial dependency it is necessary to keep these intermediate images and write the modification algorithms in a data-flow manner.

2.1.2 Temporal Processing

The implementation of temporal operators is essential for extracting motion from a video sequence. In a simple classical implementation of a first order differentiation, at least two frames taken at different instants are kept in memory, past and present images, and an operator computes results taken into account both images. When a third new complete image is taken then there is a shift between these images, the past image being replaced by the present image (already in memory) and the present image is replaced by the new acquired image, this one becoming the new present image. No matter how many changed pixels are in a new image. The temporal operators are applied even if there are no new computations to make. In the case of a pipelined hardware implementation, all the pixels of all the intermediate images stored as input for computing a derivative stage, must be replaced.

Within a SCD camera the system works in a different way. Now there are no more full-frame incoming images. Afterwards, only a set of changing pixels (acquired at the same time) are read out. Because these pixels have been taken at the same time the concept of instant can be kept and transformation to the SCD formalism is relatively straight forward.

As an example, let $I(t)$ be the past image and $I(t+1)$ the present image in the video sequence. In the classical approach, a temporal derivative can be approached in the simplest way as the subtraction between both images, this operation being performed for the n pixels in the image.

$$\left.\frac{dI}{dt}\right|_{x,y} \approx \Delta I_{x,y} = I_{x,y}(t+1) - I_{x,y}(t) \quad (3)$$

Only the subtraction operation must be performed for the n' read-out pixels, which are the changing pixels, in the SCD approach. Additionally, only the new pixel $I_{x,y}(t+1)$ must update the image $I(t)$, replacing the old value in the image. If this differentiation is made with intermediate images the process is identical. A changing intermediate pixel triggers the updating in its temporal operator, the intermediate value being updated in the source image. More complex operators such as a second derivative can be discomposed into simpler spatial and temporal derivatives. Figure 2 shows the comparison between the differential operation using both the classical and the SCD methods. In the case of a pipelined hardware implementation, only the changing pixels of the intermediate images stored as input for computing a derivative stage, must be replaced.

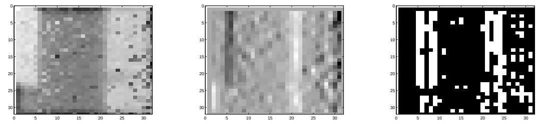
Other functions, as are non-parametric transforms, are converted into the SCD formalism in the same way. Each new pixel triggers the related operations, taken into account its contribution into the result image of each stage.

3 A SIMPLE MOTION DETECTION ALGORITHM

A moving edges detection algorithm for showing the SCD methodology has been implemented by software (Boluda et al., 2011). The algorithm is very simple and works only in structured scenarios. The idea of this experiment was not to contribute to the motion detection in terms of accuracy or robustness. The main idea was just to show how the SCD approach can accelerate an image processing algorithm. The algorithm computes the mean velocity of a single object in a scene by detecting its edges through a convolution mask, and then calculating its temporal variation subtracting them between two successive frames. If this difference is greater than a certain threshold, depending on the scene, then this pixel is taken into account as belonging to the object. Assuming a rigid object with a translation movement, the velocity of the moving edges will coincide with the object velocity. Velocity data (u,v) are available in this example when the third image has been completely processed. Aft er that, a new pair of velocity components will be available after each new image has been processed. The response of the system for updating the value of the (u,v) pair will be the acquisition time of a full image plus its transmission time and the algorithm computing time for the whole image. No matter the number of changes that have been produced in the image. All the operations will be performed systematically for all the pixels in the image.

3.1 Selective Change-Drive Software Version

The SCD version of the algorithm described previously was written (by software) in a data-flow manner, following the rules described in this section. In this version the SCD camera acquires an image at instant t and sends the triplet: gray level intensity $I_{x,y}$, together with its coordinates (x,y), of the changing pixels. As an extreme case, if there is not any moving object, there will not be any gray level change, and thus there will not be any delivered pixel and the system will not process anything. In the other extreme case, if all the intensity values have changed, all the pixels will be sent and processed, giving no advantage in terms of reduction of computations. Nevertheless, it is shown experimentally that even with a high ratio of changing pixels, a valuable speed-up with the SCD system is achieved. Details about the SCD implementation in terms of pseudo code can be found in (Boluda et al., 2011).



(a) SCD image (b) Intermediate edges image (c) Bynarized edges difference image

Figure 3: Reconstructed images from the SCD data flow.

3.2 Experimental Results

They have been performed several experiments with 32x32 pixel simulated images and with the real pixel flow obtained from the SCD camera. First of all the algorithm accuracy must be tested. That is, in a controlled environment, and with images taken from a conventional camera, the classical and the SCD algorithm versions were tested. For the SCD version, the data flow was simulated from a conventional camera, giving exactly the same results both algorithms.

Following, the system was checked with the SCD camera. Figure 3 shows several images from the performed experiment. In this experiment, a vertical strip was placed over a small vehicle moving horizontally from right to left. The scene may appear simple, but with a 32x32 sensor complex objects are not recognizable and simpler geometric forms are ideal for testing purposes.

The image shown in Figure 3 (a) is the accumulative image that has been reconstructed by adding the changing pixels delivered by the SCD camera. The image is noisy, since strategies for correcting the image quality in CMOS imagers (fixed pattern noise, etc.) have not been applied in order to show real images supplied by the SCD sensor. A simple Sobel filter for the x coordinate transformed to the SCD formalism has been applied, as shown in section 2.1.1, to implement the filter stage. The image shown in Figure 3 (b) shows edges correctly detected as well as some spurious small edges corresponding to noisy pixels. Finally, Figure 3 (c) shows the bynarized edges difference image from the last stages of the SCD algorithm. From successive difference images, the velocity components (u,v) are obtained as the center of mass of the moving edges. There is some accuracy loss in the velocity data due to the presence of noisy pixels that are contributing to the position of the object. Nevertheless, the reasons for this loss of accuracy, due to the use of real images, will be corrected in further versions of the camera firmware, applying image im-

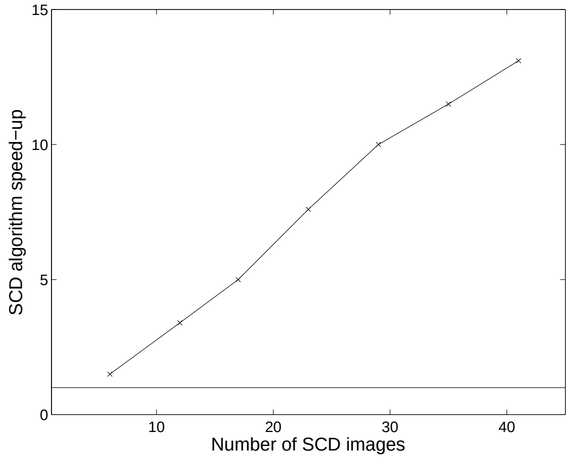


Figure 4: Speed-up execution time of the SCD algorithm versus the original implementation.

proving strategies for CMOS visual sensors.

Figure 4 shows the speed-up obtained with the performed experiment by software. Clearly, the speed-up will depend of the number of changing pixels. With fewer changing pixels, less redundant operations will perform the SCD algorithm compared to the classical version and the algorithm speed-up will increase. In the moving edge sequence, there is an average of roughly 50% of pixels that change. Therefore, we can see that we do not need a low quantity of changing pixels to obtain a valuable speed-up with this strategy.

Figure 4 shows the achieved speed-up with the SCD algorithm versus the classical version, in function of the number of frames. The speed-up increases with the number of images due that there is a fixed cost per image in the classical algorithm: computations are performed whether or not there are any changing pixels and thus the related computations are needed. This cost is always greater than the SCD algorithm cost in each image. The speed-up asymptotically will approach the quotient between the cost of both algorithms, original and SCD. This quotient has been computed, giving a theoretical speed-up of roughly 300. Therefore, Figure 4 really shows the initial part of an asymptote that, as the number of images increases, approaches its speed-up to the ideal value of 300. This speed-up depends on the experiment: objects velocity, illumination conditions, etc. A deeper explanation and analysis of the moving-edge experiment (in its software version) can be seen at (Boluda et al., 2011).

4 HARDWARE VERSION

In this position paper we claim that the motion detection algorithm in the SCD version can be implemented into a data-flow architecture, and this is our current work: to implement all this ideas into a hardware-based platform. All the experiments performed until now have been made by software achieving, nevertheless, a valuable speed-up.

It must be considered that the SCD formalism is a special case of data-flow architectures, where each incoming pixel change triggers the related operations. Figure 5 shows a schema of the proposed pipelined architecture, currently being developed into an ALTERA FPGA-based board. The pipeline has 5 stages, having as input of the first stage the SCD pixel flow, that is, the triplet formed by the grey level together with their coordinates: (I,x,y). The output of the system are the (u,v) velocity components.

The first stage just updates the SCD image with the pixels coming from the SCD camera. The SCD image is stored in a 32x32 array of 1-byte registers. The second stage is fired when the new pixel replaces the old one. This second stage computes the pixel contribution of the new pixel to the convolution image. The incoming pixel contributes to 8 pixels in the convolution image following the equation 2, since the chosen Sobel filter has a mask of 3x3 pixels.

Stage 3 stores changes into one of the two following register banks. The update image at instant t has information of the most important changes produced at this instant, but also includes changes produced in the past. Each time the camera acquires a new image, the stage switches the storage bank. The older image is replaced by the new one with the new pixels when the updating of the newer frame has been finished. Then the newer frame can be updated again with the changes coming from the precedent stage.

Stage 4 reads the two frames and marks the corresponding coordinate of a pixel pair (binarized image) if the difference is greater than a certain threshold that depends on the experiment. Stage 5 computes the centre of mass of the contributing points and makes the subtraction to the centre of mass of the preceding image. The velocity components (u,v) are then delivered as the result of the algorithm.

5 CONCLUSIONS

In this position paper we propose a change-driven processing architecture for image processing as an alternative to full-frame processing systems. This alternative will speed-up classical motion analysis al-

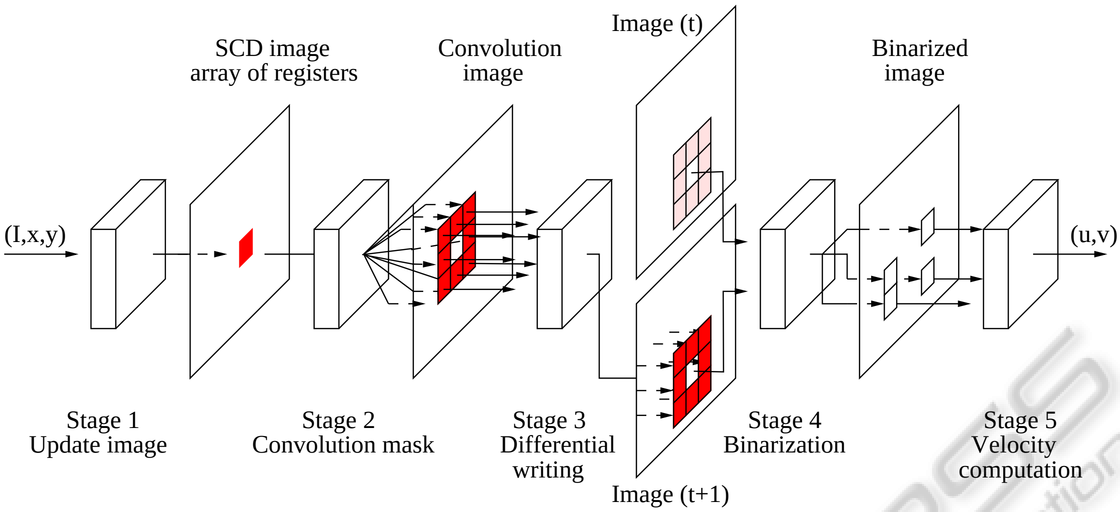


Figure 5: Data-flow pipeline.

gorithms since it reduces the total amount of computations performed. The recently developed 32x32 CMOS sensor delivers the changing pixels from the present frame to the last sent frame at each integration time. Several theoretical studies following this strategy were presented in the past with real images constructed from the original SCD data-flow. The current paper presents some ideas for implementing an already made SCD software implementation into a FPGA-based platform.

There appear as a natural continuation to this experiments performed by software, the principles of data-flow processing and architectures. Within these architectures a pixel fires the instructions that depend on it, instead of following the imperative programming model. The change-driven processing strategy presented in this paper follows these ideas.

This kind of system is oriented to real-time image processing, or systems that need very high speed processing. The SCD strategy will deliver non-redundant data, and the data-flow processing system will perform, precisely, the needed computations, with the lowest latency possible. Further versions of the SCD camera firmware, and further sensors with greater resolution, will provide the potential for the implementation of much more complex and accurate algorithms that will operate at the highest possible speed.

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