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# MOTION DETECTION: FAST AND ROBUST ALGORITHMS FOR EMBEDDED SYSTEMS

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## ABSTRACT

This article introduces a new hierarchical version of a set of motion detection algorithms called  $\Sigma\Delta$ . These new algorithms are designed to preserve as much as possible the computational efficiency of the basic  $\Sigma\Delta$  estimation, in order to target real-time implementation for low power consumption processors and embedded systems.

**Index Terms**— Motion detection, Sigma-Delta filtering, Embedded systems, Real-Time implementation.

## 1. INTRODUCTION

The growing interest for developing fully automatic video surveillance systems has recently renewed the interest for fast and reliable motion detection algorithms. Such algorithms must partition the pixels of every frame of the image sequence into two classes: the *background*, corresponding to pixels belonging to the static scene (label: 0), and the *foreground*, corresponding to pixels belonging to a moving object (label: 1).

A motion detection algorithm must discriminate the moving objects from the background as accurately as possible, without being too sensitive to the sizes and velocities of the objects, or to the changing conditions of the static scene. For long autonomy and discretion purposes, the system must not consume too much computational resources (energy and circuit area) [1]. As it involves a great amount of data - like any image processing module - the motion detection is certainly the most computationally demanding function of a video surveillance system.

Background subtraction techniques have been the object of much attention for years [2]. Recently, we have proposed a new type of methods based on  $\Sigma\Delta$  estimation [3]. These methods are very attractive from a computational point of view since they work on any size fixed-point arithmetic using only comparison, increment and absolute difference, while being as robust as other mono-modal statistical estimation methods (e.g. Gaussian estimation), whose computation is much more costly.

Different modified versions of the basic  $\Sigma\Delta$  algorithm have been proposed since then. The purpose of this paper is to review and compare them and also to introduce a new hierarchical version.

## 2. $\Sigma\Delta$ BACKGROUND SUBTRACTION

The basic principle of the  $\Sigma\Delta$  algorithm is to estimate parameters of the background using  $\Sigma\Delta$  modulation, which is a very common tool in analog-to-digital conversion: Considering a time-varying signal  $f_t$  (continuous or discrete), we estimate a discrete signal  $d_t$  by quantizing the time indexes  $\{t_i\}_{i \in \mathbb{N}}$ , and then performing at every time index  $i$  the following update formulas:

If  $d_{t_{i-1}} < f_{t_i}$  then  $d_{t_i} = d_{t_{i-1}} - \varepsilon$  else  $d_{t_i} = d_{t_{i-1}} + \varepsilon$  where  $\varepsilon$  is the discretization step (least significant bit) of  $d_t$ .

In  $\Sigma\Delta$  background subtraction, the input signal is the value of every pixel over time  $I_t$ , from which we compute the first  $\Sigma\Delta$  background estimator  $M_t$ . Then the values of the absolute differences  $|I_t - M_t|$  are used to compute the second  $\Sigma\Delta$  background estimator  $V_t$ , which is a parameter of dispersion.

### 2.1. Basic $\Sigma\Delta$ algorithm

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#### Algorithm 1: Basic $\Sigma\Delta$

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```
1 foreach pixel  $x$  do [step #1:  $M_t$  estimation]
2   if  $M_{t-1}(x) < I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) + 1$ 
3   if  $M_{t-1}(x) > I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) - 1$ 
4   otherwise  $M_t(x) \leftarrow M_{t-1}(x)$ 
5 foreach pixel  $x$  do [step #2:  $O_t$  computation]
6    $O_t(x) = |M_t(x) - I_t(x)|$ 
7 foreach pixel  $x$  do [step #3:  $V_t$  update]
8   if  $V_{t-1}(x) < N \times O_t(x)$  then  $V_t(x) \leftarrow V_{t-1}(x) + 1$ 
9   if  $V_{t-1}(x) > N \times O_t(x)$  then  $V_t(x) \leftarrow V_{t-1}(x) - 1$ 
10  otherwise  $V_t(x) \leftarrow V_{t-1}(x)$ 
11   $V_t(x) \leftarrow \max(\min(V_t(x), V_{max}), V_{min})$ 
12 foreach pixel  $x$  do [step #4:  $\hat{E}_t$  estimation]
13   if  $O_t(x) < V_t(x)$  then  $\hat{E}_t(x) \leftarrow 0$  else  $\hat{E}_t(x) \leftarrow 1$ 
```

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In the basic version (Alg. 1), the  $\Sigma\Delta$  background  $M_t$  and  $\Sigma\Delta$  variance  $V_t$  are updated every frame, according to the comparison with the current image  $I_t$  and current absolute difference  $O_t$  respectively.  $N$  is an amplification factor for  $V_t$ , allowing then to compute the motion label  $\hat{E}_t$  by simply comparing  $O_t$  and  $V_t$  (typical values of  $N$  are between 1 and 4).  $V_{min}$  and  $V_{max}$  are two parameters used to control the

overflow of  $V_t$  that could happens if some pixels are saturated (due to sensor over-exposition). Their typical values are 2 and  $2^m - 1$  respectively (where  $m$  is the number of bits of the representation). Note that this *clipping* is a modification not present in the original version [3].

## 2.2. Improved algorithm: conditional $\Sigma\Delta$

**Algorithm 2:** Conditional  $\Sigma\Delta$

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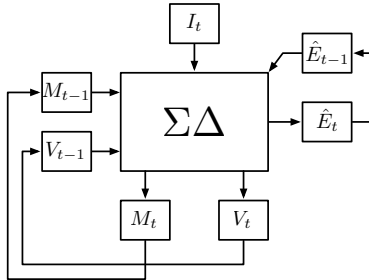
```

1 foreach pixel  $x$  with do [step #1': conditional  $M_t$  update]
2   if  $\hat{E}_{t-1}(x) = 0$  then
3     if  $M_{t-1}(x) < I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) + 1$ 
4     if  $M_{t-1}(x) > I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) - 1$ 
5     otherwise  $M_t(x) \leftarrow M_{t-1}(x)$ 
6   else
7      $M_t(x) \leftarrow M_{t-1}(x)$ 
8 foreach pixel  $x$  do [step #2:  $O_t$  computation]
9    $O_t(x) = |M_t(x) - I_t(x)|$ 
10 foreach pixel  $x$  do [step #3:  $V_t$  update]
11   if  $V_{t-1}(x) < N \times O_t(x)$  then  $V_t(x) \leftarrow V_{t-1}(x) + 1$ 
12   if  $V_{t-1}(x) > N \times O_t(x)$  then  $V_t(x) \leftarrow V_{t-1}(x) - 1$ 
13   otherwise  $V_t(x) \leftarrow V_{t-1}(x)$ 
14    $V_t(x) \leftarrow \max(\min(V_t(x), V_{max}), V_{min})$ 
15 foreach pixel  $x$  do [step #4:  $\hat{E}_t$  estimation]
16   if  $O_t(x) < V_t(x)$  then  $\hat{E}_t(x) \leftarrow 0$  else  $\hat{E}_t(x) \leftarrow 1$ 

```

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The conditional version (Alg. 2 and Fig. 1) uses relevance feedback from the estimated position of the moving objects at the previous frame, given by  $\hat{E}_{t-1}$ . It consists in updating the  $\Sigma\Delta$  background  $M_t$  and/or the variance  $V_t$  only for the pixels  $x$  considered background (i.e. where  $\hat{E}_{t-1}(x) = 0$ ). It prevents moving object from integrating the background and/or modifying the noise variance [4].



**Fig. 1.** conditional  $\Sigma\Delta$

## 2.3. Zipfian estimation

The Zipfian version (Alg. 3) [5] is based on the relation between the  $\Sigma\Delta$  estimation and the statistical estimation, using

a Zipf-Mandelbrot distribution, which implies that the updating frequency of the background should be proportional to the dispersion of the distribution (variance). In that version, we first compute a threshold which varies according to the frame index  $t$ :  $\rho$  is the value of the index *modulo*  $2^m$  ( $m$  is the number of bits of the representation).  $\pi$  is the value of the greatest power of 2 which divides  $\rho$ . Finally the threshold  $\sigma$  is equal to  $2^m$  divided by  $\pi$ . The result is that pixels  $x$  such that  $V_t(x) > 2^{m-k}$  will be updated every  $2^{k-1}$  frames, for  $k \in \{1, m\}$ . To avoid auto-reference, the variance  $V_t$  is updated using a constant period  $T_V$  (usually a power of 2 between 1 and 64).  $T_V$ , like the amplification parameter  $N$ , can be automatically adjusted using a simple noise estimation method, which consists in counting the number of isolated pixels in the estimated labels  $\hat{E}_t$ .

**Algorithm 3:** Zipfian estimation

---

```

1 [step #0: variance threshold computation]
2 find the greatest  $2^p$  that divides  $(t \bmod 2^m)$ 
3 set  $\sigma = 2^m / 2^p$ 
4 foreach pixel  $x$  do [step #1'': conditional  $M_t$  estimation]
5   if  $V_{t-1}(x) > \sigma$  then
6     if  $M_{t-1}(x) < I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) + 1$ 
7     if  $M_{t-1}(x) > I_t(x)$  then  $M_t(x) \leftarrow M_{t-1}(x) - 1$ 
8     otherwise  $M_t(x) \leftarrow M_{t-1}(x)$ 
9   else
10     $M_t(x) \leftarrow M_{t-1}(x)$ 
11 [foreach pixel  $x$  do [step #2:  $O_t$  computation]
12    $O_t(x) = |M_t(x) - I_t(x)|$ 
13 foreach pixel  $x$  do [step #3'': update  $V_t$  every  $T_V$  frames]
14   if  $t \bmod T_V = 0$  then
15     if  $V_{t-1}(x) < N \times O_t(x)$  then
16        $V_t(x) \leftarrow V_{t-1}(x) + 1$ 
17     if  $V_{t-1}(x) > N \times O_t(x)$  then
18        $V_t(x) \leftarrow V_{t-1}(x) - 1$ 
19     otherwise  $V_t(x) \leftarrow V_{t-1}(x)$ 
20      $V_t(x) \leftarrow \max(\min(V_t(x), V_{max}), V_{min})$ 
21 foreach pixel  $x$  do [step #4:  $\hat{E}_t$  estimation]
22   if  $O_t(x) < V_t(x)$  then  $\hat{E}_t(x) \leftarrow 0$  else  $\hat{E}_t(x) \leftarrow 1$ 

```

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## 2.4. New hierarchical algorithm

The hierarchical algorithm (Fig. 2) is a bi-level version of  $\Sigma\Delta$  filtering. Each  $\Sigma\Delta$  block implements the basic algorithm #1 of the algorithm #3. Both blocks are using conditional update. At the low level it is a conditional *temporal* update:  $M_t^1$  and  $V_t^1$  are updated depending on  $\hat{E}_{t-1}^1$ . At the high level, it is a conditional *spatial* update:  $M_t^0$  and  $V_t^0$  are updated depending on  $\hat{E}_t^0$ , the oversampling binary mask of  $\hat{E}_t^1$ . The subsampling factor is in the range [2, 10] and is set accordingly to the “size” of the clutter noise. Finally, a morphological post-processing is applied in two steps. The first one

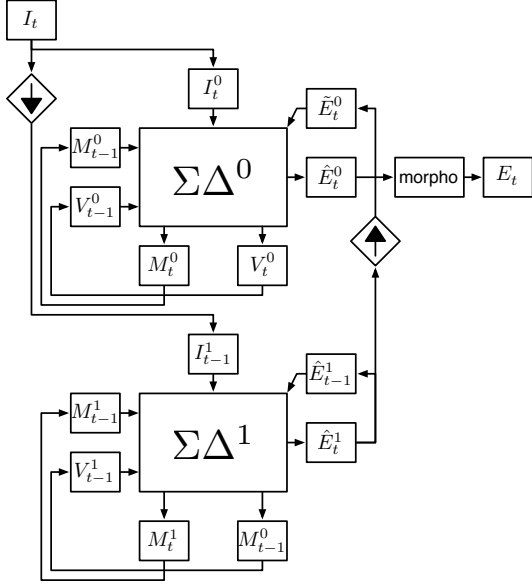


Fig. 2. hierarchic  $\Sigma\Delta$

removes stand-alone pixels that are considered as noise, the second one is a  $3 \times 3$  morphological closing.

### 3. BENCHMARK



Fig. 3. Hall sequence, images 38, 91, 170, 251

In order to evaluate the impact of the modifications on the performance of these algorithms, a RoC analysis has been done with the *Hall* sequence (Fig. 3) than can be considered as a *difficult* sequence because of the radial movement of non-rigid objects (people). The Ground Truth has been drawn for 4 images of that sequence. Given  $TP$  the True Positive,  $TN$  the True Negative,  $FP$  the False Positive and  $FN$  the False Negative, we compute the Matthews Correlation Coefficient

(Eq. 1) instead of accuracy or product of  $TP$  ratio by  $TN$  ratio because the two classes (motion and background) are of very different size. It returns a value between  $-1$  (perfect inverse segmentation) and  $+1$  (perfect segmentation) while 0 signifies a wrong segmentation.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (1)$$

A set of 32 algorithms (combinations of parameters) has been evaluated. Figures (Tab. 1) are provided for only four of them:  $\Sigma\Delta$  is the basic algorithm (Fig. 4),  $\Sigma\Delta$ +Zipf (Fig. 5) is the basic algorithm with Zipfian estimation, Conditional  $\Sigma\Delta$  (Fig. 6) is the best mono-level algorithm with conditional update (with or without Zipfian estimation) and Hierarchical  $\Sigma\Delta$  (Fig. 7) is the best two-level algorithm with conditional update. For this benchmark, the decimation factor for sub-sampling and oversampling was set to 8 and the Zipfian  $V_t$  update period  $T_V$  was set to 4.

algorithm	38	91	170	251	average
<i>MCC without morphological post processing</i>					
$\Sigma\Delta$	0.495	0.347	0.169	0.282	0.323
$\Sigma\Delta$ +Zipf	0.676	0.600	0.366	0.308	0.487
Conditional $\Sigma\Delta$	0.424	0.533	0.555	0.590	0.526
Hierarchical $\Sigma\Delta$	0.644	0.663	0.468	0.415	0.548
<i>MCC with morphological post processing</i>					
$\Sigma\Delta$	0.811	0.657	0.372	0.596	0.609
$\Sigma\Delta$ +Zipf	0.830	0.728	0.547	0.449	0.639
Conditional $\Sigma\Delta$	0.754	0.764	0.530	0.385	0.608
Hierarchical $\Sigma\Delta$	0.816	0.827	0.686	0.582	0.728

Table 1. Results:  $MCC$  scores for 4  $\Sigma\Delta$  algorithms with/without morphological post processing

Considering first, the results *without* post morphological processing, each evolution has better results than the previous one. The best *conditional* version is obtained with Zipfian estimation combined with the conditional update of  $M_t$  and  $V_t$ . The best *hierarchical* version is obtained with the best *conditional* version combined with a conditional update of  $M_t^1$  at low level. Considering then the results *with* morphological post processing, all results are in progression except for image # 170 that corresponds to radial movement of the first person. Both visual and numerical results enforce the use of morphological post-processing (Fig. 8) to remove remaining noise. Another benchmark, not presented here, has been done on a sequence with cars. The results were better but harder to differentiate, as such a kind of sequence is easier to segment.

### 4. CONCLUSION

We have presented a new hierarchical and conditional motion detection algorithm based on an evolution of previous  $\Sigma\Delta$  algorithms. Preliminary results show better (visual and



Fig. 4. basic  $\Sigma\Delta$



Fig. 6. conditional  $\Sigma\Delta$



Fig. 5.  $\Sigma\Delta$  + Zipf



Fig. 7. Hierarchical  $\Sigma\Delta$

quantitative) performances for difficult sequences with radial movement and non-rigid object. As its complexity remains low this algorithm is well suited for very light embedded systems. Future work will consider other *difficult* sequences with the presence of clutter like snow, rain or moving trees.

## 5. REFERENCES

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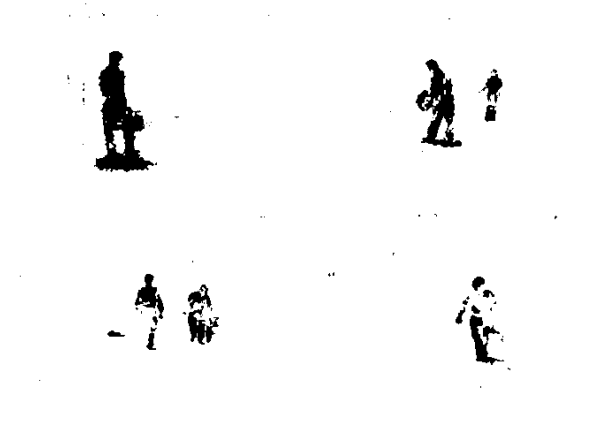


Fig. 8. Hierarchical  $\Sigma\Delta$  + Morpho