

# Unsupervised Camera Motion Estimation and Moving Object Detection in Videos

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**Abstract**— In this article, we consider the robust estimation of a location parameter using M- estimators. We propose here to couple this estimation with the robust scale estimate proposed in [Dahyot and Wilson, 2006]. The resulting procedure is then completely unsupervised. It is applied to camera motion estimation and moving object detection in videos. Experimental results on different video materials show the adaptability and the accuracy of this new robust approach.

**Keywords**—estimation, object detection, parameter.

## I. INTRODUCTION

Many problems in computer vision involve the separation of a set of data into two classes, one of interest in the context of the application and the remaining one. For instance, edge detection in images requires the thresholding of the gradient magnitude to discard noisy flat areas from the edges. The challenge is then to automatically select the appropriate threshold [Rosin, 1997].

Regression problems also involve the simultaneous estimation of the variance or standard deviation of the residuals/errors. The presence of a large number of outliers makes difficult the estimation of the parameters of interest. Performance of robust estimators is highly dependent on the setting of a threshold or scale parameter, to separate the good data (inliers) that fit the model, from the gross errors (outliers) [Chen and Meer, 2003]. The scale parameter, needed in M-estimation and linked to the scale parameter of the inliers residuals, is often set a priori or estimated by the Median Absolute Deviation. In [Dahyot and Wilson, 2006], a robust non-parametric estimation for the scale parameter has been proposed and then combined with a robust RANSAC [Fischler and Bolles, 1981] for object recognition. This paper proposes to combine the robust scale parameter estimation with a M-estimation of the camera motion parameter in videos. The whole scheme is unsupervised. The estimated scale parameter is also used to detect moving objects in the sequences.

## II. ROBUST SCALE ESTIMATION

### II.1 Observations

The observations consist in a set of independent samples  $\{x_i\}$  of a random variable  $X$ . Its probability density function can be written as a mixture:

$$P_X(x|a, 0) = V_X(x|a, 0, C) \cdot P_X(C) + P_X(x|C) \cdot P_X(x|C) \dots (1)$$

with the pdf  $V_X(x|a, 0, C)$  corresponding to a particular class  $C$  of interest (inliers) that depends onto one scale parameter  $a$  and possibly also on a location parameter  $0$ . The other pdf  $P_X(x|C)$  in the mixture is generated by possible outliers occurring in the observations (class  $C$ ) and the parameters of interest  $a$  and  $0$  do not depend on those outlying observations.  $V_X(C)$  is the proportion of inliers and  $V_X(C)$  is the proportion of outliers.

In this work, we assume the distribution of the inliers to be a Generalized centered Gaussian [Aiazzi et al., 1999]:

$$p_{X(x|C, a, 0)} = \frac{2\Gamma(a)}{\Gamma(a)^2} \exp\left(-\frac{|x|}{a}\right) \frac{1}{a} \dots (2)$$

with  $p=a^{1/a}$

Setting the shape parameter  $a = 1$  (Laplacian law) and  $a = 1/2$  (Gaussian law) in equation (2), are two popular hypotheses [Hasler et al., 2003, Dahyot et al., 2004]. We assume  $a$  is known and focus on the estimation of the scale  $a$  and  $0$ .

### II.2 Robust scale estimation knowing the location parameter 0

We now assume that we have  $n$  independent variable  $X_n$  of the same nature of the  $X$  previously defined. Samples for each  $X_n$  can be easily obtained for instance by splitting the original sample set of samples  $\{x_i\}$  into  $n$  sets. Depending on the applications, the  $n$  random variables can also be naturally defined (see section 3). We define the variables:

$$Z = \frac{1}{n} \sum_{i=1}^n |X_i|^{1/C} Y = Z^a \dots (3)$$

Inliers of  $Z$  and  $Y$  (in class  $C$ ) are the samples  $Z_j$  or  $y_j$  computed with  $n$  independent samples of  $X$  such that  $V_i, x_i \in C$ . For  $n = 1$  and  $Z = |X|^{1/a}$ , the pdf  $V_Z(z|0, a, C)$  corresponds to the gamma distribution:

$$V_Z(z|0, a, C) = \frac{1}{\Gamma(a)} \frac{z^{a-1}}{a^a} \exp\left(-\frac{z}{a}\right) \quad z > 0 \dots (4)$$

When  $n > 1$ , the pdf  $V_Z(z|C, a)$  is the gamma function

$G_Z(z|C, a)(z)$ , and the *pdf* of  $Y$  can easily be inferred [Dahyot and Wilson, 2006]. The maximum of the distributions  $V_Z(z|C, a)$  and  $V_Y(y|C, a)$  can be then computed:

$$Z_{\max C} = p \cdot (na - 1), \quad na > 1$$

$$Y_{\max C} = [(n - 1) a p]^a, \quad n > 1$$

Those maxima depend on the parameter  $a$  by definition of  $p$  (cf. eq. (2)). From equation (5), the scale  $a$  can be computed by:

$$a_Z = \frac{Z_{\max C}}{p} = \frac{Z_{\max C}}{p} \cdot \frac{r(3a)}{T(O)}^{1/2} \quad na > 1$$

$$a_Y = \frac{Y_{\max C}}{(n-1)a} = \frac{r(3a)}{T(av)}^{1/2} \quad n > 1$$

The maximum of the distributions of  $Y$  and  $Z$  has first to be located. Depending on the proportion and the values of the outliers, the localization of the maximum needed in the estimation gets more difficult. We assume that the relevant maximum for the estimation is the closest peak to zero in the distributions  $V_Y(y|a, 9)$  and  $V_Z(z|a, 9)$ . 2.3 Computation of the scale estimate in practice. The scale estimates are computed using the mean shift procedure on the set of samples of variables  $Y$  or  $Z$ , starting from the minimum sample value (or starting from zero). More details are presented in [Dahyot and Wilson, 2006]. However, in some signal processing applications, the digitized signal is discrete with known quantized levels in a finite domain. For instance, pixel values in video data are integers in  $[0; 255]$ . Most of all, the variable  $Z$  (or  $Y$ ) has its values in a one-dimensional space. Therefore, as an alternative to the kernel representation of the distribution and the Mean Shift algorithm to perform the estimation, standard histograms can be easily used and their derivatives easily computed using filters. This is another practical and faster way to perform the estimation when dealing with a digitized signal. Both  $Y$  and  $Z$  perform similarly robust scale estimation (see [Dahyot and Wilson, 2006]).

### III. APPLICATIONS

Section 3.1 presents an experiment for unsupervised moving object detection in static sequences. The variable  $Z$  is used for the scale estimation, there is no location parameter  $d$  (the camera motion is null) and the shape parameter is chosen  $a = 1$ . Section 3.1 extends those preliminary results to camera motion estimation and moving object detection. The variable  $Y$  is used for the scale estimation, the location parameter  $d$  corresponds to a 6-dimensional camera motion vector and the

shape parameter is chosen  $a=1/2$ .

#### III.1 Application to moving object detection in static camera sequences

##### III.1.1 Using colour video data $n = 3$

We are considering two different colour images  $I_t = (R_t, G_t, B_t)$  and  $I_{t'} = (R_{t'}, G_{t'}, B_{t'})$  from a video sequence. The samples of the random variables  $X_n$  for  $n \in \{1, 2, 3\}$  are computed as the inter-frame difference on each colour band for each position  $i$  of the pixel:

$$X_1 : x^{(1)} = R_t(i) - R_{t'}(i) \quad X_2 : x^{(2)} = G_t(i) - G_{t'}(i) \quad X_3 : x^{(3)} = B_t(i) - B_{t'}(i) \quad \dots\dots\dots(7)$$

$$Z : z_i = |x^{(1)}| + |x^{(2)}| + |x^{(3)}| \quad (2) \quad \dots\dots\dots(3)i$$

The distribution of  $Z$  has been drawn using a histogram over the samples  $\{z_i\}$  in figure 1(a). The estimated distribution of the inliers  $P_Z(z|C, a_Z)$  is also superimposed (with a rescaling factor to match the maxima).

##### III.1.1.1 Using grey level video data $n = 2$

When the sequence is grey level, the samples of the variable  $Z$  can be computed using the backward and forward inter-frame differences:

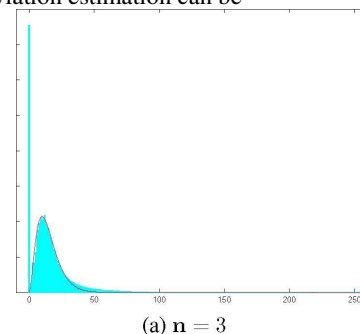
$$X_1 : x^{(1)} = I_t(i) - I_{t-1}(i) \quad X_2 : x^{(2)} = I_{t+1}(i) - I_t(i) \quad \dots\dots\dots(8)$$

$$Z : z_i = |x^{(1)}| + |x^{(2)}|$$

Figure 1 (b) shows the distribution of  $Z$  in this case.

##### III.1.1.1.1 Results

When comparing images from a video, the interframe differences contain outliers due to camera and object motion. However in most applications, it can be assumed that a sensible proportion of pixels are matching. This proposed scheme for standard deviation estimation can be



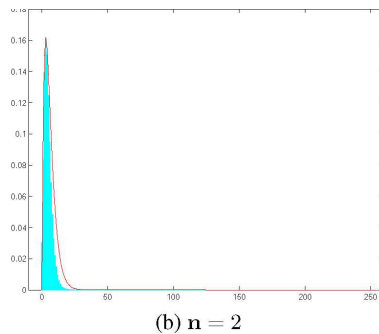


Figure 1: Distribution ( $z$ ) (blue bars) with the fitted distribution of the inliers ( $z_C, a_z$ ) on real video data for inter-frame difference analysis.

used on the inter-frame differences in order to separate or locate the outliers in the observations. We are considering in this example a video recorded from a static camera. Only moving objects in the scene generate outliers. By setting a threshold using the estimated standard deviation, the moving objects are located using the decision rule  $z_i > n \cdot 3 \cdot a$  for each pixel position  $i$ .

Figure 2 shows an example of the moving object detection process. The inter-frame difference is computed between the median frame of the video as a model of the background model of the scene, and the frame at time  $t = 100$ . Segmentation of the movement is not perfect as it is only based on the pixel statistics. Some pixels from the moving objects have similar values as the background ones at the same location, therefore their differences are classified as inliers (un-moving regions). However, it is a simple method to roughly locate moving regions which, in this example, are objects of interest such as pedestrians and cars for a traffic surveillance application. A result on a grey level sequence is shown in figure 3.

### III.II Application to unsupervised camera motion estimation and moving object detection in moving camera sequences

We consider in this section the problem of camera motion estimation from video data. Camera motion estimation has many applications such as video restoration and content analysis [Bouthemy et al., 1999, Kokaram et al., 2003, Coldefy et al., 2004]. The motion parameters are 6-dimensional to take into account zoom, rotation and translation. The residuals  $\{x_i\}$ , corresponding to the displaced frame difference ( $dfd$ ), are linearly depending on the camera motion parameters  $\theta$ . Figure 5 shows two successive images in a sequence and their difference, respectively before and after camera motion compensation. Those two observations correspond to the residuals observed at the first and the last iteration of our robust estimation. Images of videos used for testing are shown in fig. 4.

#### III.II.I Iterative estimation of the scale and location parameters

For each iteration, we estimate the scale parameter  $a_\gamma$  on the set of residuals and then perform the estimation of the motion parameters until convergence:

Initialisation  $\theta^{(0)}$

Repeat :

Scale estimation on  $\{y_i\}_M$

$\theta^{(m+1)} = \arg \min_j \hat{p}^{(m)} \text{ Until convergence } \theta^{(m)} ; (U^m)_p$

.....(9)

computed from  $\{x_i(\theta^{(m)})\}$



Frame at  $t = 100$



Median image of the sequence as *background*



Figure 2: Colour sequence. Detection of moving objects (in red) based on the statistics of the difference of the colour pixels with the median image of the sequence (sequence dtneu-winter).



$t = 199$



$t = 200$

(a)

(b)

Figure 3: Grey-level sequence. Detection of moving objects in between successive frames, based on the statistics of the difference of grey level pixels.

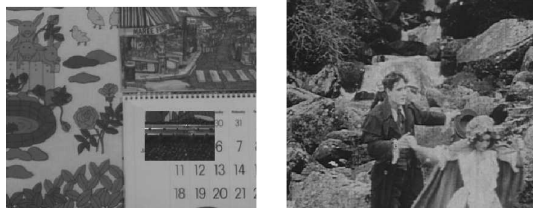


Figure 4: Videos used in the test. (a) is a simple video where the camera motion is known, and the dark rectangle is the only (outlier) object that moves differently from the background. (b) is a shot from an old film where several artifacts occur (blotch, flicker, sporadic and severe vertical displacement, etc).

The location parameter estimation is performed using M-estimation with a robust function  $p$  [Dahyot and Kokaram, 2004]. The initial guess  $0^{(0)}$  is estimated using non-robust least squares.

**Scale parameter estimation.** Using the set of residuals  $\{x_i\}$  samples of the variable  $X$ , we need first to define variable  $Y$  and to compute its samples. The residuals are a mixture of inliers and outliers as being defined in this article. The proportion  $a$  of inliers is unknown and the outliers correspond to unmatched pixels due, for instance, to moving objects (different movement to the camera motion), occlusions or artifacts (specially in old films). The outliers form localized areas in the  $dfd$  (cf. figure 5). Using this property, we draw samples of the random variable  $Y$  such as  $y_i = \hat{x}_i + x_{i+1}$  where  $x_i$  and  $x_{i+1}$  are two neighbouring residuals in the  $dfd$ . This strategy allows to preserve a similar proportion of inliers in the observations  $\{y_i\}$ . Using our estimation scheme with histograms for a faster computation, the scale parameter is set to  $a_y = 3 \times a_v$ . This choice insures that 99% of the inliers are kept for the estimation of the camera motion parameters.

**Accuracy of the estimates.** Using video (a) (cf. figure 4) where the ground truth is known, the scale parameter and the motion parameters are estimated while adding gaussian noise of variances 10 and 100. Compared to the ground truth, the motion parameters are estimated with a Mean Square Error below 0.00007 on zoom-rotation parameters and 0.05 pixels on the translation parameters. The estimated scale parameter of the class of inliers is also stable over the sequence: the standard error of the estimate  $a_y$  of one grey level compared to the ground truth.

**Scale Adaptability.** On the video (b) (cf. fig. 4), our unsupervised robust camera motion estimation is also performed. No ground truth is known, however the estimated parameters are coherent with the one with a manually tuned estimation. The estimated scale parameter of the inliers in the  $dfd$  remains constant over 400 frames of the sequence (b). 10 frames show a slight over-estimation of the scale. Those artifacts correspond to sudden changes in the intensity values (flicker) that increase the  $dfd$  [Kokaram et al., 2003]. The automatic SD estimation allows to account for those changes

in the data stream. The algorithm proposed in (9) has also always converged in our experiments undertaken on different videos.

### III.II.II Moving object detection

Figure 5 shows an example with two successive images from a video of cricket. The images of the residuals are also shown before and after motion compensation. The estimated scale  $a_y$  allows taking a decision in between pixels being outlier residuals (in black) and pixels being inliers residuals (in white). Those binary maps allows the detection of independent moving objects in the sequence, and carry relevant information, for instance, for video understanding [Coldefy et al., 2004]. Our method provides an automatic thresholding method that does not require to manually set a threshold over the weights as in [Coldefy et al., 2004].

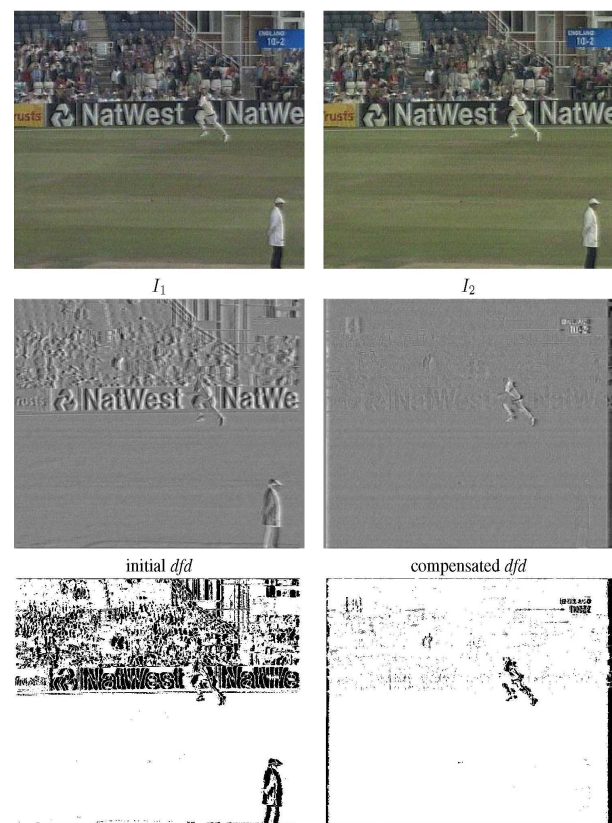


Figure 5: Application to camera motion estimation. Top: two successive images from a sport video. Middle: corresponding image of residuals when the motion is not compensated (left), and when it is compensated (right). Bottom: maps of the outliers (residuals above  $3 \times a_y$ ).

## IV. FUTURE WORK

In this article, we proposed an unsupervised method for camera motion estimation and moving object detection in video. The whole objects are not detected but only its parts that generate outliers in the *dfd*. Future work will aim at improving the segmentation of the moving objects by using mathematical morphology and/or hysteresis thresholding to take into account spatial correlation between neighbouring pixels.

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