Technique to model the movement of the scene using image sequence

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Abstract. The paper proposes a technique to model the movement of a scene based on backward stochastic gradient pixel-by-pixel estimation of the deformation field. Calculation of the moving object’s area is considered as the task of testing the hypothesis that the image grid nodes belong to the area of motion. The paper presents the estimated two kinds of errors: false positive and false negative. The obtained results are compared with the results of the MVFAST algorithm. The increase in the signal-to-noise ratio of the image of a moving object is achieved by combining the frames of the video sequence under study. To combine conjugate points, high-speed recurrent algorithms are used that do not require a priori information. The paper presents an example of estimation of object’s trajectory parameters using the technique. The interframe geometric deformations of the video sequence are used as intermediate parameters of the trajectory.

1. Introduction

One of the problems of digital video processing is the detection of changes in the sequence of image. The study of this problem is devoted to a large number of works, in particular [1-3] and many others. Part of this problem is the evaluation of the scene motion along the sequence of images. Some tasks require the only detection of the motion, while others – extraction of the moving object or the motion area boundary. One of the biggest challenges is to estimate the trajectory of a moving object by finding its parameters. In this case, all the information needed to determine motion parameters of the object is extracted from the frames of a video sequence.

There are various approaches to identify an area of moving object based on the interframe difference [4, 5], background subtraction [5, 6], the use of statistics [5, 7], block estimation [8, 9], optical flow analysis [10]. As a rule, the processing can be presented as an estimation of interframe geometric deformations of two images, one of which can be considered as the reference image \( Z^s = \{z^s_{i,j}\} \) and the second as a deformed image \( Z^d = \{z^d_{i,j}\} \), where \( z^s_{i,j} \) is the value in the node \((i,j)\) of a grid, which represents the image. The field \( H = \{h_{i,j}\} \) of interframe shift vectors \( h_{i,j} \) of all points of the reference image corresponding to the nodes of the sample grid will be called deformation field. When finding estimates of \( h_{i,j} \) the approach of using stochastic gradient estimation [11-13] on the
deformed image of the coordinates \((x, y)\) of the conjugate points of the reference image corresponding to its nodes is promising.

The estimates of the projections \(h_{(i,j)x}\) and \(h_{(i,j)y}\) of the shift vector on the basis axis of the image can be written \([14]\):

\[
\mathbf{h}_{i,j} = \mathbf{h}_{i,j} - \lambda h \text{sign}(\mathbf{h}_{i,j}) \beta_{ij}, \quad i = 1, N_x, \quad j = 1, N_y, \quad (1)
\]

where \(\lambda_h\) is a coefficient, which determines the rate of change of the estimated parameters; \(\mathbf{h}\) is the gradient estimation of an objective function; \(N_x \times N_y\) is the size of the image.

An expression similar to (1) can also be written when representing the interframe shift vectors in polar form: \(\mathbf{h}_{i,j} = (\rho_{i,j}, \phi_{i,j})\), where \(\rho_{i,j}\) is the length of the vector, \(\phi_{i,j}\) is the angle with respect to the \(x\) axis. In \([15]\), it was shown that, due to the inertia of changes in estimates, the use of parameters \(\rho_{i,j}\) and \(\phi_{i,j}\) in the stochastic gradient estimation of the deformation field does not give equivalent estimates if compared to the use of \(h_{(i,j)x}\) and \(h_{(i,j)y}\). This is since the sets of parameters have different physical meaning.

In \([16]\), two approaches to the synthesis of the algorithms for estimating the deformation field based on backward estimation \([17]\) are proposed and investigated. In the first approach, the stochastic gradient procedure sequentially processes all rows of an image to find estimates of shifts for all points of the reference image. It processes each row bidirectionally i.e. from the left to the right and from the right to the left. Subsequent joint processing of the obtained results \([16]\) allows compensating inertia of the stochastic estimation. The second approach also takes into account the correlation of the rows of the image. To do this, it processes rows one after the other with a change in direction after each row and uses obtained values to form a resulting estimate for each node. As criteria for the formation of the resulting estimate, the minimum of gradient estimation of the objective function and the correlation maximum of local neighborhoods of the deformed and reference images were investigated.

In this paper we investigate the effectiveness of several algorithms for estimating the deformation field, considered in \([16]\), to solve the problems of extracting of a moving object from a video sequence and estimating parameters of its trajectory. Let us denote these algorithms as:

- **REFMPP** (Reverse Estimation of the Field of Motion by Polar Parameters) algorithm – reverse estimation without taking into account the correlation of adjacent rows of the image when using polar parameters as a set of parameters for the shift vector;
- **CEFMP** (Correlation Estimation of the Field of Motion by Projections) algorithm – an estimation that does take into account the correlation of adjacent rows when using projections on the basis axes of the image as a set of parameters for the shift vector;
- **CEFMPP** (Correlation Estimation of the Field of Motion by Polar Parameters) – an estimation that does take into account the correlation of adjacent rows when using polar parameters as a set of parameters for the shift vector.

To compare the results, a well known blocking algorithm MVFAST (Motion Vector Field Adaptive Search Technique) \([18]\) was used.

### 2. Detection of motion areas using the deformation field

Detecting areas of moving objects in the image is an important step in determining movement parameters. Errors at this stage when determining, for example, the trajectory of a moving object can lead to incorrect estimations of such parameters like speed, the direction of object movement, etc.

Detection of the area of motion using the deformation field can be considered as a task of testing the hypothesis of the image nodes belonging to a moving object. Then, as a result of the threshold processing, two kinds of errors are possible: of the first kind (false positive) – the assignment of a background pixel to the area of motion, and of the second kind (false negative) – the assignment of a pixel of a motion area to the background. This raises the problem of selecting the appropriate detection threshold.
For correctness, we will conduct a study using the same images used in [16]. These are two adjacent frames of a video sequence (Figure 1), in which the car, located in the center, moves in a straight line, and the car on the right does not move. The parameters of the interframe spatial shift of a moving vehicle: \( h_x = 3 \), \( h_y = 2.95 \) or in the polar system: \( \rho = 4.2 \), \( \varphi = 45^\circ \).

Figure 1. An example of adjacent frames of a video sequence with a moving object.

Figures 2a-2c show examples of motion detection in images of Figure 1 when the deformation field is formed by the REFMPP algorithm and three thresholds: \( \max 1.0 \rho \), \( \max 3.0 \rho \) and \( \max 8.0 \rho \), where \( \max \rho \) - the maximum value of the shift vector’s length. It is clear that for \( \max 1.0 \rho \) threshold there are practically no errors of the second kind. For the threshold \( \max 3.0 \rho \) the number and size of falsely detected areas of motion decrease while gaps appear in the area of motion. For \( \max 8.0 \rho \) threshold the number of errors increases sharply near the borders of the moving object and in its low-contrast areas. Similar results for the CEFMPP algorithm are shown in Figures 2d-2f. It can be seen that at the \( \max 0.1 \rho \) and \( \max 0.3 \rho \) thresholds falsely detected areas are practically absent. When the threshold is set to \( \max 0.8 \rho \) gaps appear on the object borders. In general, if the parameters of interframe geometric deformations are reduced to a parallel shift, the CEFMPP algorithm gives the best results: there are no false detections, and the skips in motion area occur only at a significant threshold value.

![Figure 2](image)

Figure 2. The result of threshold processing.

Motion detection for a more complex model of interframe deformations is complicated by the fact that for a certain combination of deformation parameters shift vector’s length will be close to zero. This is well illustrated by the results (Figure 3) of detecting the area of motion for the case when the right image of Figure 1 was modeled so that the deformations of the moving object correspond to the parameters of the similarity model: \( \mathbf{h} = (2,3)^T \), \( \varphi = 4^\circ \), \( \kappa = 1 \). Figures 3a and 3b show the results at the \( 0.05 \rho \text{max} \) threshold for cases of deformation field formation by the CEFMP and CEFMPP algorithms, respectively. Figure 3c shows results at the \( 0.1 \rho \text{max} \) threshold for the CEFMPP algorithm. It is seen...
that as the threshold is increased, the non-detected area of the image around the center of rotation also increases. The CEFMPP algorithm gives the best results.

Figure 3. The result of threshold processing for the case of complex motion.

Figure 4 shows the probability distributions of the interframe shift vectors length estimates of the nodes of the reference image for the experiment. Figure 4a corresponds to the MVFAST algorithm, Figure 4b – to the REFMPP algorithm, Figure 4c – to the CEFMPP algorithm. Dotted graphs correspond to the distribution of estimates in the area without motion, solid graphs – in the motion area. The true value of the interframe shift vector length for all nodes in the motion area is the same and is \( \rho_{s} = 4.2 \). The threshold is found as a compromise between the probability of errors of the first and second kind. For example, Figures 4d-4e present the empirical graphs of dependences of the probabilities of errors of the second kind on the threshold value. For 0.05\( \rho_{\text{max}} \) threshold value, the probability of error of the first kind is 0.052\% for the MVFAST algorithm and 0.047\% for the CEFMPP algorithm. For the REFMPP algorithm, the probability of first kind errors decreases to 0.05\% when the threshold is increased up to 0.12\( \rho_{\text{max}} \). Thus, in the considered example, when forming the deformation field by the mentioned above algorithms, errors of the first kind can be almost eliminated at small values of the threshold.

Figure 4. The dependences of the probability distribution of the shift length and the probability of errors of the second kind on threshold values.

It is also seen from figure 4d that the second-type error probability for the MVFAST algorithm does not decrease to zero even at small threshold values. For example, at the threshold 0.1\( \rho_{\text{max}} \) the probability of the second kind error for the MVFAST algorithm is 3.33\%. For comparison, the probability of a second kind error for the REFMPP algorithm does not exceed 0.01\%, for the CEFMPP algorithm it does not exceed 0.03\%. Thus, the probability of missing motion areas when using the MVFAST algorithm is much higher. Using the above data, the optimal threshold value was found, by the criterion of the minimum of the sum of probabilities of the first and second kind errors, equal to 0.2\( \rho_{\text{max}} \), at which the probabilities of the first and second kind errors for the CEFMP algorithm were 0.033\% and 0.035\%, and for the CEFMPP algorithm – 0.01\% and 0.07\%, for the MVFAST algorithm – 0.052\% and 3.5\%, respectively. Thus, the probability of the second kind error for the MVFAST algorithm is more than an order of magnitude higher than for the CEFMPP algorithm.
By threshold processing of the deformation field, we can select the contour of a moving object. Figure 5 shows the contour and the area of the moving object, obtained by threshold processing at the critical value of the criterion for the no-motion hypothesis equal to $0.2\rho_{\text{max}}$. To select the contour, morphological operations of closing and filling were used [19]. Figures 5a and 5b correspond to the CEFMP and CEFMPP algorithms, respectively; Figure 5c corresponds to the MVFAST algorithm with a block size of one pixel.

![Figure 5. The result of the moving object area calculation.](image)

The figures confirm the above conclusions that the probability of errors of the first kind when using stochastic gradient estimation even at small thresholds is close to zero, in contrast to the MVFAST algorithm. At the same time, the MVFAST algorithm provides insignificant probabilities of errors of the second kind. For the CEFMPP algorithm, even with small interframe shifts of a moving object (1.5-2 pixels) in the studied examples, the probability of error of the first kind of motion detection was 0.5-1.5%, of the second kind – 0.2-1.0%. This makes it preferable for solving problems of detecting an area and a contour of a moving object.

### 3. Estimation of parameters of a moving object trajectory

The object trajectory can be estimated using parameters estimates of a certain model of interframe geometric deformations, obtained from the deformation field in the area of motion. Moreover, if the motion parameters of an object are characterized only by a parallel shift, then the shift of each pixel in the area of motion coincides with the interframe motion of the object. Let us consider a more complex motion, in particular, the similarity model with the parameters $(h_x, h_y, \kappa, \phi)^T$ and the affine model with the parameters $(a_{00}, a_{01}, a_{10}, a_{11}, h_x, h_y)^T$ [20]. Estimates of model parameters for the selected area of motion can be found at:

For the similarity model:

$$
\hat{h}_x = N_{\text{ma}}^{-1} \sum_{i,j \in \text{MA}} \hat{h}_{(i,j)}, \quad \hat{\phi} = -\arctg \frac{\text{c} \text{ov}(\hat{h}_{(i,j)}, y) - \text{c} \text{ov}(\hat{h}_{(i,j)}, x)}{\sigma_x + \sigma_y + \text{c} \text{ov}(\hat{h}_{(i,j)}, x) + \text{c} \text{ov}(\hat{h}_{(i,j)}, y)},
$$

$$
\hat{h}_y = N_{\text{ma}}^{-1} \sum_{i,j \in \text{MA}} \hat{h}_{(i,j)}, \quad \hat{\kappa} = \sigma_x \left( \cos \phi \sigma_x + \text{c} \text{ov}(\hat{h}_{(i,j)}, x) + \sin \phi \sigma_y + \text{c} \text{ov}(\hat{h}_{(i,j)}, y) \right),
$$

for affine model:

$$
\hat{a}_{00} = N \sigma \sigma - \text{c} \text{ov}^2(x, y) + 1, \quad \hat{a}_{01} = N \sigma \text{c} \text{ov}(\hat{h}_{(i,j)}, y) - \text{c} \text{ov}(x, y) \text{c} \text{ov}(\hat{h}_{(i,j)}, x) + 1, \quad \hat{a}_{10} = N \sigma \text{c} \text{ov}(\hat{h}_{(i,j)}, x) - \text{c} \text{ov}(x, y) \text{c} \text{ov}(\hat{h}_{(i,j)}, y) + 1, \quad \hat{a}_{11} = N \sigma \text{c} \text{ov}(\hat{h}_{(i,j)}, y) - \text{c} \text{ov}(x, y) \text{c} \text{ov}(\hat{h}_{(i,j)}, x) + 1,
$$

$$
\hat{h}_x = N_{\text{ma}}^{-1} \left( \sum_{i,j \in \text{MA}} \hat{h}_{(i,j)} - (\hat{a}_{00} - 1) \sum_{i,j \in \text{MA}} (x - x_0) - \hat{a}_{01} \sum_{i,j \in \text{MA}} (y - y_0) \right),
$$

$$
\hat{h}_y = N_{\text{ma}}^{-1} \left( \sum_{i,j \in \text{MA}} \hat{h}_{(i,j)} - \hat{a}_{10} \sum_{i,j \in \text{MA}} (x - x_0) - (\hat{a}_{11} - 1) \sum_{i,j \in \text{MA}} (y - y_0) \right),
$$

where: $N = \sigma_x \sigma_y - \text{c} \text{ov}^2(x, y)$; $\text{c} \text{ov}(a, b) = N_{\text{ma}}^{-1} \sum_{i,j \in \text{MA}} a_i b_j - N_{\text{ma}}^{-2} \sum_{i,j \in \text{MA}} a_i \sum_{j \in \text{MA}} b_j$, $\sigma_a = N_{\text{ma}}^{-1} \sum_{i,j \in \text{MA}} (a - M(a))^2$, MA is an area containing image nodes assigned to a moving object, $N_{\text{ma}}$ – the number of these nodes.
Figure 6 shows the estimates of the deformation field generated by the MVFAST algorithm (Figure 6a), the CEFMP algorithm (Figure 6b) and CEFMPP algorithm (Figure 6c) for the situation when the object movement corresponds to the parameters of the similarity model: $h = (2,3)^T$, $\phi = -\pi/4$, $\kappa = 1$.

![Figure 6. Deformation field under deformations corresponding to the similarity model.](image)

For the detected area of motion, we estimate the parameters: for the situation of using the CEFMP algorithm using formulas (2): $\hat{h}_x = 1.98$, $\hat{h}_y = 3.04$, $\hat{\phi} = -4.08^\circ$, $\hat{\kappa} = 1.002$, for the CEFMPP algorithm: $\hat{h}_x = 1.77$, $\hat{h}_y = 2.61$, $\hat{\phi} = -3.3^\circ$, $\hat{\kappa} = 0.988$. Both sets of estimates have high accuracy, but greater accuracy is provided by the use of the CEFMP algorithm, which is explained by the lower inertia of the estimates when using this algorithm. At the same time, this algorithm provides less accurate detection of the area of a moving object. Using the obtained estimates, it is easy to find the parameters of the trajectory of the object and predict its position on subsequent frames.

To find the estimates of the parameters, as a rule, it is enough to use only a small part of the nodes in the area of motion. For example, using only 1% of randomly selected nodes of a moving object area, we obtain for the CEFMP algorithm: $\hat{h}_x = 2.03$, $\hat{h}_y = 3.27$, $\hat{\phi} = -3.91^\circ$, $\hat{\kappa} = 0.995$, for CEFMPP algorithm: $\hat{h}_x = 1.81$, $\hat{h}_y = 2.46$, $\hat{\phi} = -3.41^\circ$, $\hat{\kappa} = 0.992$. The accuracy of these estimates is close to the situation of using all nodes in the area of motion. Thus, the relative errors of the estimates of shifts increased by 0.5% and 7.5%, the error of the angle estimate – by 0.25%, and the error of the scale – by 0.45%. At the same time, computational costs have been significantly reduced. Note that the estimates obtained using the deformation field generated by the MVFAST algorithm: $\hat{h}_x = 1.03$, $\hat{h}_y = 4.58$, $\hat{\phi} = -2.04^\circ$, $\hat{\kappa} = -2.04^\circ$, are much worse.

For more complex motion, an affine model can be used. Figure 7 shows the estimates of the deformation field generated by the MVFAST algorithm (Figure 7a) and the CEFMP algorithm (Figure 7b) and CEFMPP algorithm (Figure 7c) for the situation when the true values of the parameters are $a_{00} = 0.95$, $a_{01} = 0.02$, $a_{10} = -0.08$, $a_{11} = 0.98$, $h_x = 1$, $h_y = 1$.

![Figure 7. Deformation field for the affine deformation model.](image)

Using expressions (3) for the case of applying the CEFMPP algorithm, we obtain the estimates: $\hat{a}_{00} = 0.935$, $\hat{a}_{01} = 0.011$, $\hat{a}_{10} = -0.044$, $\hat{a}_{11} = 0.987$, $\hat{h}_x = 1.63$, $\hat{h}_y = 0.73$, $\hat{\kappa} = (1.63, 0.73)^T$; and for the CEFMP algorithm estimates are: $\hat{a}_{00} = 0.952$, $\hat{a}_{01} = 0.021$, $\hat{a}_{10} = -0.086$, $\hat{a}_{11} = 0.981$, $\hat{h}_x = 1.15$, $\hat{h}_y = 1.22$. Here the estimates of the parameters are also closer to the true values when projections of
the shift vector to the basis axes of the image are used. When the deformation field is formed by the MVFAST algorithm, the estimates of the parameters are significantly different from the true values: \( \hat{a}_{00} = 0.987, \hat{a}_{01} = -0.031, \hat{a}_{10} = 0.141, \hat{a}_{11} = 0.961, \hat{h}_x = 2.27, \hat{h}_y = -0.66 \). Using this algorithm to find the trajectory of a moving object using a video sequence is not very promising.

4. Conclusion
Calculation of the moving object’s area is considered as the task of testing the hypothesis that the image grid nodes belong to the area of motion. As a result of the threshold processing, two kinds of errors occur: of the first kind (false positive) – the assignment of a background pixel to the area of motion, and the second kind (false negative) – the assignment of a pixel of a movement area to the background. It is shown that backward stochastic gradient pixel-by-pixel estimation of the deformation field provides the high accuracy of moving object area detection when the threshold value is selected based on the required probabilities of error of the first and the second kind. Taking into account the inter-row correlation significantly improves the accuracy of the moving object area detection. Experimental studies have shown that the formation of the deformation field using pixel-by-pixel stochastic gradient estimation provides the best results in detecting the area of motion compared to the MVFAST algorithm, especially in terms of the probability of errors of the second kind.

It is possible to effectively estimate the parameters of the object's trajectory using the deformation field in the area of motion. The estimates of interframe geometric deformations are used as a source of information to estimate the parameters of the trajectory. Expressions to find estimates of the parameters of the similarity and affine models for a detected area of motion are obtained. The accuracy of estimates of the parameters is greater when projections of the shift vector to the basis axes of the image are used to form the deformation field, due to lower inertia of their estimates. At the same time, this approach gives less accuracy in detecting the area of a moving object, which must be taken into account when solving specific problems. It is shown that with minor losses in accuracy in estimating the parameters (fractions of a percent), only a small local sample of nodes of the motion area of the deformation field can be used.

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