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PARAMETRIC MOTION ESTIMATION BASED ON LOW COMPLEXITY IMAGE REGISTRATION ALGORITHM

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Abstract*:* Parametric motion estimation is an important task for various video processing applications, such as analysis, segmentation, and coding. However, the main disadvantage of standard approaches to parametric motion estimation (PME) is the increased computational complexity with the higher degree of motion models when compared to block-based local motion estimation approaches. The method in this paper, proposes new low complexity PME algorithm. In proposed algorithm, full-precision images are replaced with 1 bit-per-pixel images which allows many of the arithmetic operations in the standard PME approach to be replaced with logic operations.

Keywords: Motion estimation, image registration, low complexity

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INTRODUCTION

Image registration is an important component in many image processing applications. Motion estimation is widely used and even essential part in various video coding algorithm. One important recent application is for the estimation of global motion parameters for object-based video coding [1]. The process of estimating parameters that describe background deformation through camera motion is often referred to as in more general case, parametric motion estimation (PME). PME is an important task for various video processing applications, such as analysis, segmentation, and coding. The black matching algorithm is one of the most widely used for motion estimation in various video coding algorithm[2].

The process for an estimation has to satisfy three requirements. It has to be fast, accurate, and robust in the presence of arbitrarily moving foreground objects. There are two main techniques adopted to estimate these parameters: feature-based and intensity-based. However, the main drawback of these approaches is the increased computational complexity of the optimization techniques required to estimate up to eight global motion parameters simultaneously. This increased computational complexity becomes critical for devices with low processing capabilities, e.g., portable and wireless devices. Various applications for PME include video coding and filtering, object segmentation in video sequences, or analysis issues, such as classification by motion and summarization of scene content.

The proposed method in this paper concentrate on the problem of reducing the computational complexity of this type of registration while maintaining the accuracy of the resulting global motion fields. This paper, proposes a new low complexity PME algorithm. In proposed algorithm, full-precision images are replaced with 1 bit-per-pixel images which allows many of the arithmetic operations in the standard PME approach to be replaced with logic operations.

III. BACKGROUND

The basic principle of every PME technique is to find a parametric motion module(PMM) representing the background transformation between two given frames. As background regions are assumed to be planar geometric objects, 3×3 homographies can represent such a transformation with high precision. These homographies can be calculated in different ways. One possibility is to reduce the background registration error directly. Another possibility is to obtain local motion models describing the translational motion of background area parts. By combining these local motion models in an appropriate manner, a higherorder motion description, containing zoom, shear, rotation, translation, and perspective deformation, can be derived. Another possibility is to generate motion vector fields by feature detection and tracking. Both kinds of motion vector fields describe the displacement of background regions as well as the arbitrary motion of foreground objects. When the macroblock or feature motion vectors belonging to foreground objects are defined as outliers, the process of finding a higher-order background motion model can be seen as a robust regression problem. As the determination of such parametric models from local motion models can be done linearly, utilizing linear regression methods for outlier removal is a reasonable option. Although the motion model may not be linear.

A. Linear Regression in General

The task of linear regression in general is to find a model for a set of N observations. This model can be repre- sented by a set of linear equations connecting the p parameters of the model θ with the observations (y ↔ X)

$y_i = x_{i,1} \cdot \theta_1 + \cdots + x_{i,p} \cdot \theta_p.$ (1)

A model parameter set $\hat{\theta}$ can be estimated by

$\hat{y}_i = x_{i,1} \cdot \hat{\theta}_1 + \cdots + x_{i,p} \cdot \hat{\theta}_p$ (2)

The regression task is then modified to minimize the sum of estimation errors $r_i = y_i - \hat{y}_i$, each rated by an error function $\rho(r_i)$. The most common ρ is the square function, leading to least squares (LSs) solution

$\min_{\hat{\theta}} \sum_{i=1}^{N} r_i^2$ (3)

This simple error-weighting function is often not useful for estimating a parametric background motion model out of local motion. A single outlier in a set of local motion models would lead to severe misestimation. Neve- rtheless, when applied to a set of noisy inliers in terms of very small local motion estimation errors, LS is able to deliver an unbiased result. A combination of robust outlier rejection and LS is a suitable way of implementing robust regression.

IV. PREVIOUS WORK DONE

When global motion estimation on compressed video data is needed, for instance, macroblock-based estimation approaches, working on translational motion vectors of encoded video streams are suitable. Michael Tok, Alexander Glantz, had explained monte-carlo-based parametric motion estimation using a hybrid model[3] Approach a two-step hybrid PME scheme for simplifying Monte-Carlo-based PME on encoded video data streams as well as on feature vector fields generated by feature tracking on raw pixel data. This scheme uses motion models with differing parameter amounts and so reduces the complexity of the whole estimation process dramatically. The usability of this methodology was that it was fast, accurate, and robust in the presence of arbitrarily moving foreground objects but the algorithm was having higer complexity. The another method called motion estimation without integer pal search proposed by Lang Li[4].Since the NS entirely removes the integer-pel search, the area cost of hardware encoder could be significantly reduced, and the power consumption can also be greatly reduced consequently. It is worth noting that the remarkable improvement on area and power cost is not achieved at obvious performance loss. It was also not much effective in parametric motion estimation. After that Salih Dikbas and Yucel Altunbasak proposed a novel true-motion estimation algorithm[5] which was focused on video processing applications, such as motion-compensated temporal frame interpolation (MCTFI) or motion-compensated frame rate up-conversion (MCFRUC). But method was having a much lower memory bandwidth utilization than the benchmark methods

This paper proposes parametric motion estimation algorithm based on low complexity image registration In proposed algorithm, full-precision images are replaced with 1 bit-per-pixel images which allows many of the arithmetic operations in the standard GME approach to be replaced with logic operations.

V. PROPOSED METHODOLOGY

In this paper Low complexity GME algorithm is proposed which include.

Use Low Bit-Depth Images

In low-complexity algorithm the complexity is first reduced by reducing the precision of the target and reference images I and R. The precision of these images is reduced to two bits by taking only the two most significant bits (MSB) for every pixel. By reducing the precision of E and ∇E to 1 bit, these multiplication operations can be converted into simple XOR logic operations. The basic concept that allows multiplication to be replaced by XOR can be understood by observing the sign of the product of E and ∇E for the 8-bit case as shown in Table I. Note that multiplication between positive and negative numbers produces a negative result, whereas the XOR operation between “1” and ‘0’ produces “1” which ideally should be “0” if multiplication is to be replaced with XOR. To resolve this problem, the thresholding operation is opposite for E and ∇E. The logic value of the XOR terms and their product is shown in Table II.

TABLE I

$\widetilde{E}\imath$	$\nabla\widetilde{E}_\imath$	$\widetilde{E}\imath \oplus \nabla\widetilde{E}_\imath$
-	-	+
-	+	-
+	-	-
+	+	+

TABLE II

E_i	∇E_i	E_i x ∇E_i
-	-	+
-	+	-
+	-	-
+	+	+

In low bit-depth images, interest is whether the errors are positive, negative, or zero. If method assume that there is an approximately equal number of positive and negative gradients in the images to be registered then, when the two images are perfectly registered, the number of positive errors should be approximately equal to the number of negative errors. However, a problem occurs when there are a large number of pixels where (I ̃ = R̃ (i.e., zero error pixels). If the 1-bit error is calculated using the formula

$$\tilde{E} = \begin{cases} 1, & \widetilde{E}\imath < \tilde{R}\mathrm{i} \\ 0, & \widetilde{E}\imath \geq \tilde{R}\mathrm{i} \end{cases} \qquad (4)$$

Our solution is to define a positive error image Ẽj and a negative error image Ẽ-i as follows:

$$\tilde{E}_i^{+} = \begin{cases} 1, & \tilde{E}_i < \tilde{R}_i \\ 0, & \tilde{E}_i \geq \tilde{R}_i \end{cases} \qquad \tilde{E}_i^{-} = \begin{cases} 1, & \tilde{E}_i \leq \tilde{R}_i \\ 0, & \tilde{E}_i > \tilde{R}_i \end{cases} \qquad (5)$$

Defining the positive and negative error images in this way means that, for zero error pixels, the two terms in following equation(6)will cancel each other and hence these pixels will have no effect on the final value of $\nabla K(m)$.

$$\frac{\partial K}{\partial m_j} = \sum_{i=1}^{N} \tilde{E}_i^{+} \oplus \frac{\partial \tilde{E}_i}{\partial m_j} - \sum_{i=1}^{N} \tilde{E}_i^{-} \oplus \frac{\partial \tilde{E}_i}{\partial m_j}. \qquad (6)$$

The precision of the steepest descent images is reduced as follows:

$$\frac{\partial \tilde{E}_i}{\partial m_j} = \begin{cases} 1, & \frac{\partial E_i}{\partial m_j} > 0 \\ 0, & \text{otherwise.} \end{cases} \qquad (7)$$

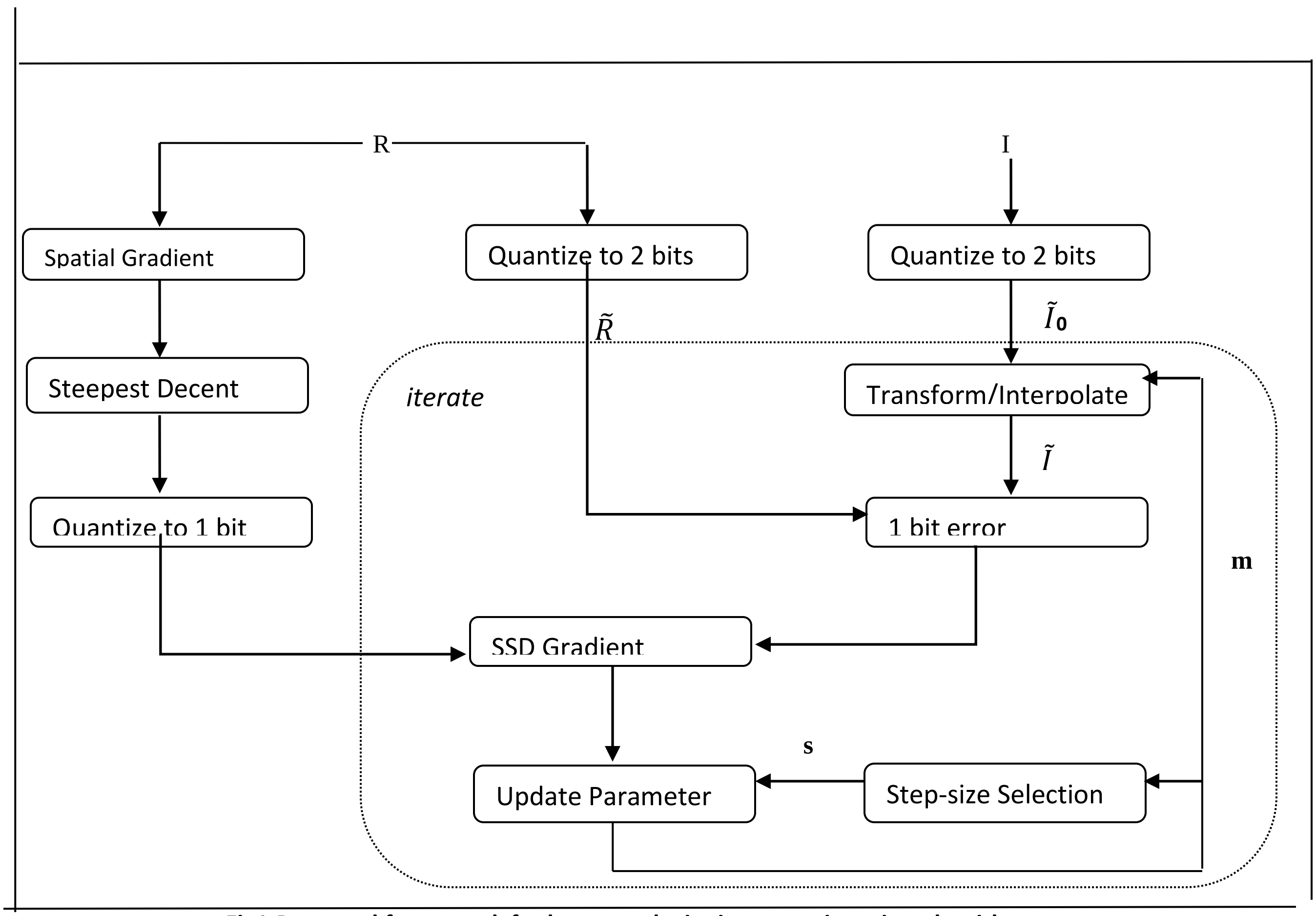

Fig1.Proposed framework for low complexity image registration algorithm

Adaptive Update of the Step Size

Equation (6) will produce an accurate estimate of the sign of the elements of ∇K(m) however, when using 1-bit versions of the steepest-descent and error images, the Hessian of K(m) is no longer valid. In the standard GN method, ∇K(m) provides the direction in which to proceed to reach the global minimum and the Hessian provides the size of the step taken in that direction. So with our 1-bit estimation algorithm, the size ofthe step toward the global minimum is no longer available. Hence to calculate p the following equation is used:

$$p = -s \times \text{sign}(\nabla K(m)) \qquad (8)$$

To ensure convergence of the algorithm in the absence of he Hessian authors first fix the initial step-size for each motion parameter. The step-size is then halved when one of the following conditions is met for a particular step-size value: 1) all motion parameters converge before the maximum number of iterations is reached; 2) the maximum number of iterations (7) is reached with this step-size value. A motion parameter is considered to have converged when the sign of the element of ∇K(m) for that parameter has changed three times in three consecutive iterations. One added advantage of this method is that the calculation of the Hessian matrix and its inverse are no longer required which increases the overall speed of the algorithm. Fig. 1 shows a block diagram of the ALC algorithm.

VI. POSSIBLE OUTCOME

A parametric motion estimation based on a low complexity image registration may improve and lowers the complexity of parametric motion estimation. Achieves the same registration accuracy as the standard PME approach but with significantly reduced computational complexity. With this implementation hardware based performance cannot predicted until its real implementation on hardware platform.

VII. CONCLUSION

The unique features of the proposed algorithm are: replacement of arithmetic operations with logical operations, complete elimination of the Hessian matrix calculation and an adaptive step-size procedure for each gradient descent operation. Our approach uses logic operations rather than arithmetic operations should may simplify hardware implementations of the algorithm. The registration accuracy and success rate of our method is not significantly different to other state-of-the-art techniques.

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