

A Robust Global Motion Estimation for Digital Video Stabilization

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Abstract. This paper proposes a global motion estimation method to remove unintentional camera motions which degrade the visual quality of image sequences. The proposed approach is based on combination of 2D Radon transform, 1D Fourier transform and 1D Scale transform which can accurately estimate scale, rotational and translational distortions of camera motion and is robust to internal moving objects. Our experimental results with real and synthesized videos indicate the effectiveness of our proposed method.

Keywords: Global Motion Estimation, Radon Transform, Fourier Transform, Scale Transform, Similarity Motion Model.

1 Introduction

Digital video stabilization methods try to eliminate unwanted camera motions. These typical high frequency motions such as pan, and jitter, degrade visual appearance quality of videos. Digital video stabilization algorithms can be divided into two main steps, Motion Estimation, and Motion Correction. In motion estimation step, the global motion between consecutive frames is determined. The motion estimation algorithms can be categorized into three main classes, Block matching based methods, Transform domain based methods, and Feature matching based methods. In the block matching based approaches [1,2], the current frame is divided into several blocks. Then, the motion for each block is estimated. Finally, the global motion is calculated using estimated block motions. The main disadvantage of this category is that local movement of internal objects degrades the accuracy of block motion estimation. High time complexity is another problem with this class of algorithms which is due to the exhaustive search for block matching. Feature matching based methods [3,4,5] extract suitable features such as SIFT [6], and SURF [7] from both current and reference frames. After determining the corresponding features, the parameters of global motion is estimated using matched features. Because of handling motions such as rotation and zooming in addition to translational motions, algorithms of this class are more accurate and flexible than block matching approaches which can

only deal with translational motions. However, feature based methods have limitation by occlusion which is due to the moving objects. High computational load for feature detection and matching is another drawback of these methods. The algorithms of the last category transform the frames into a new domain and estimate the motion parameters using the information in the transform domain. In phase correlation technique [8], the translation property of Discrete Fourier Transform (DFT) is used in order to obtain the translational motion parameters. Although this method is very fast and is robust to local motion of moving objects, it is not able to estimate rotational motion which is frequent in most shaky videos. Hong et al. [9] utilized polar transform in order to estimate rotation in addition to translation parameter of motion. Although the accuracy of this method is satisfactory, polar transform suffers from nonuniform sampling which makes it unsuitable for videos with moving objects. Being unable to handle scale distortion is another drawback of this algorithm.

The second part of a video stabilization system is motion correction where estimated global motion is filtered to remove unwanted camera movements such that the desired camera motion remains intact. Several techniques [10,11,12] have been proposed to smooth the estimated global motion. Although these methods can fulfill efficient smoothness, sometimes they may have an degrading affect on the intentional motion because of inaccurate tuning of the free parameters of the methods.

In this paper, to improve the accuracy, flexibility, and robustness of the motion estimation, we propose a novel transform domain motion estimation based on combination of 2D Radon transform, 1D Fourier and Scale transforms which can accurately estimate scaling factor in addition to rotation and translation parameters of motion. Since the Radon transform can be computed through 2D Fourier transform with the same complexity by means of the projection-slice theorem [13], and because of calculating motion parameters using 1D projections instead of 2D gray level images, our method is also applicable to realtime applications.

2 Proposed Method

As mentioned in previous section, commonly used motion estimation methods such as block matching, and transform domain based algorithms, can only deal with translational and rotational distortions. These approaches produce poor performance when the image fluctuation contains scale distortion as well as translational and rotational distortions. Although feature based methods can estimate scale parameter in addition to translation and rotation parameters of motion, these approaches are prone to feature mismatching which is due to the internal moving objects or occlusion. So, in this paper, a novel global motion estimation method based on combination of 2D Radon transform, 1D Fourier transform and 1D Scale transform is presented which can estimate the similarity

motion model parameters accurately and is robust to internal moving objects and occlusion. The similarity motion model is defined as

$$\begin{pmatrix} x_t^i \\ y_t^i \end{pmatrix} = s \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{pmatrix} x_r^i \\ y_r^i \end{pmatrix} + \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}, \quad (1)$$

where s is the scale factor, θ is the rotation angle between two corresponding points (x_r^i, y_r^i) and (x_t^i, y_t^i) in reference and target frame respectively, and $(\Delta x, \Delta y)$ denotes the displacement in x and y directions respectively.

In this section, we first describe the Radon, Fourier and Scale transforms and their useful properties, then we present our motion estimation algorithm based on combination of these transforms.

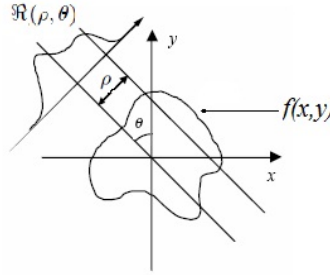


Fig. 1. Geometric illustration of the Radon transform of a 2D function

2.1 Radon Transform

Let $f(x,y)$ be a 2D image. Its Radon transform, denoted $\Re f$ is a 2D function of the real spatial variable ρ and the angular variable θ defined by

$$\Re f(\rho, \theta) = \int_{-\infty}^{+\infty} f(\rho \cos(\theta) - t \sin(\theta), \rho \sin(\theta) + t \cos(\theta)) dt. \quad (2)$$

Geometrically, $\Re f(\rho, \theta)$ is equal to the integral of the function f on the straight line passing through ρ and of direction perpendicular to θ [14]. Figure 1, illustrates the geometry of the Radon transform. The Radon transform has some properties which is useful for motion estimation. These properties are as follows.

Translation: If we denote the image translated by a vector $\vec{t}$ with components (t_x, t_y) using $f_{(\vec{t})}$ we have

$$f_{(\vec{t})}(x, y) = f(x + t_x, y + t_y). \quad (3)$$

The Radon transform of the translated image becomes

$$\Re f_{(\vec{t})}(\rho, \theta) = \Re f(\rho + t_x \cos(\theta) + t_y \sin(\theta), \theta). \quad (4)$$

Translating an image in Cartesian domain shifts the spatial variable of its Radon transform. The amount of displacement depends on both translation vector and angular variable. However for a given θ , the Radon transform of the translated image is simply equal to the translation of the Radon transform of the image with respect to the spatial variable [14].

Rotation: Denoting the rotated version of image f by angle ψ using f_ψ , we have

$$f_\psi(x, y) = f(x\cos(\psi) - y\sin(\psi), x\sin(\psi) + y\cos(\psi)). \quad (5)$$

Since the integrand of Equation (2), can be expressed using a rotation matrix, the Radon transform of the rotated image becomes

$$\Re f_\psi(\rho, \theta) = \Re f(\rho, \theta - \psi). \quad (6)$$

It is clear that a rotation in an arbitrary image in the Cartesian domain corresponds to a translation in the angular variable of its Radon transform.

Scale: let f^s be the scaled version of image f with a factor s . Then we have

$$f^s(x, y) = f(sx, sy). \quad (7)$$

The Radon transform of the scaled image is

$$\Re f^s(\rho, \theta) = \frac{1}{s} \Re f(s\rho, \theta). \quad (8)$$

Scaling an image by a factor s corresponds to scaling of its Radon transform and the angular variable ρ by $\frac{1}{s}$ and s respectively.

2.2 Fourier Transform

Let $f(x)$ be a 1D function, its Fourier transform denoted by $F_f(\omega)$ defined as

$$F_f(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x) e^{-2j\pi x\omega} dx. \quad (9)$$

This transform has many properties [15], among which the translation invariance property is suitable for motion estimation. This property can be described as follows.

if we shift a 1D function $f(x)$ by x_0 (displacement value) and denote it by $g(x)$, then we have

$$g(x) = f(x + x_0). \quad (10)$$

If we take the Fourier transform of both sides of above equation, we have

$$F_g(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x + x_0) e^{-2j\pi x\omega} dx = e^{2j\pi x_0\omega} F_f(\omega). \quad (11)$$

By taking the magnitude of two sides of equation (11), we have

$$|F_g(\omega)| = |F_f(\omega)|. \quad (12)$$

In other words, the magnitude of Fourier transform of a 1D function is translation invariant.

2.3 Scale Transform

The Scale transform of a 1D function $f(x)$ is defined as

$$\mathcal{D}_f(p) = \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} f(x) x^{-jp-\frac{1}{2}} dx, \quad (13)$$

where $p \in \mathbf{R}$ is the Scale transform parameter. The key property of the Scale transform is the scale invariance. In other words, if we define $g(x) = \sqrt{\alpha}f(\alpha x)$ a scaled version of 1D function $f(x)$ with scale factor α , then,

$$\mathcal{D}_g(p) = \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} g(x) x^{-jp-\frac{1}{2}} dx = \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} \sqrt{\alpha}f(\alpha x) x^{-jp-\frac{1}{2}} dx. \quad (14)$$

By setting $y = \alpha x$,

$$\mathcal{D}_g(p) = \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} \alpha^{jp} f(y) y^{-jp-\frac{1}{2}} dy = \alpha^{jp} \mathcal{D}_f(p). \quad (15)$$

If we take the magnitude of both sides of above equation, we have

$$|\mathcal{D}_g(p)| = |\mathcal{D}_f(p)|. \quad (16)$$

We can see from above equation that the magnitude of Scale transform is scale invariant.

2.4 Parameter Estimation

In this section we propose our motion estimation algorithm base on similarity motion model which is shown in equation (1). Consider $f_r(x, y)$ and $f_t(x, y)$ be the reference frame and target frame respectively and we assume that the target frame is transformed version of the reference frame using similarity motion model. By this assumption, the mathematical relationship between $f_r(x, y)$ and $f_t(x, y)$ is

$$f_t(x, y) = f_r(\alpha_0 \cos(\theta_0)x - \alpha_0 \sin(\theta_0)y + t_x, \alpha_0 \sin(\theta_0)x + \alpha_0 \cos(\theta_0)y + t_y), \quad (17)$$

where α_0 , θ_0 , and (t_x, t_y) are scale, rotation, and translation distortions. By taking the Radon transform of both sides of equation (17), we obtain

$$\Re f_t(\rho, \theta) = \frac{1}{\alpha_0} \Re f_r(\alpha_0 \rho + t_x \cos(\theta - \theta_0) + t_y \sin(\theta - \theta_0), \theta - \theta_0). \quad (18)$$

From equation (18), it can be seen that for every 1D radial slice $\Re f_t(\cdot, \theta)$ of the Radon transform of target frame f_t , there is a corresponding radial slice $\Re f_r(\cdot, \theta)$ of the Radon transform of reference frame f_r . Hence, for every constant $\theta' \in [0, \pi]$, if we define $g_{t, \theta'}(\rho) = \Re f_t(\rho, \theta')$ and $g_{r, \theta'}(\rho) = \Re f_r(\rho, \theta' - \theta_0)$, we have

$$g_{t, \theta'}(\rho) = \frac{1}{\alpha_0} g_{r, \theta'}(\alpha_0 \rho + d_0), \quad (19)$$

where $d_0 = t_x \cos(\theta' - \theta_0) + t_y \sin(\theta' - \theta_0)$ is the amount of displacement in variable ρ . Now, if we take the 1D Fourier transform of both sides of equation (19), we obtain

$$F_{g_{t,\theta'}}(\omega) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} \frac{1}{\alpha_0} g_{r,\theta'}(\alpha_0 \rho + d_0) e^{-2j\pi \rho \omega} d\rho. \quad (20)$$

By setting $t = \alpha_0 \rho + d_0$,

$$F_{g_{t,\theta'}}(\omega) = \frac{1}{\sqrt{2\pi} \alpha_0^2} e^{\frac{2\pi}{\alpha_0} j \omega d_0} \int_{-\infty}^{+\infty} g_{r,\theta'}(t) e^{-2\frac{\pi}{\alpha_0} j t \omega} dt = \frac{1}{\alpha_0^2} e^{\frac{2\pi}{\alpha_0} j \omega d_0} F_{g_{r,\theta'}}\left(\frac{\omega}{\alpha_0}\right). \quad (21)$$

Taking the magnitude of both side of above equation results in

$$|F_{g_{t,\theta'}}(\omega)| = \frac{1}{\alpha_0^2} |F_{g_{r,\theta'}}\left(\frac{\omega}{\alpha_0}\right)|. \quad (22)$$

By applying the Scale transform on the two sides of above equation we have

$$\mathcal{D}_{|F_{g_{t,\theta'}}|}(p) = \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} \frac{1}{\alpha_0^2} |F_{g_{r,\theta'}}\left(\frac{\omega}{\alpha_0}\right)| \omega^{-jp-\frac{1}{2}} d\omega = \alpha_0^{-jp-\frac{3}{2}} \mathcal{D}_{|F_{g_{r,\theta'}}|}(p), \quad (23)$$

or

$$|\mathcal{D}_{|F_{g_{t,\theta'}}|}(p)| = \alpha_0^{-\frac{3}{2}} |\mathcal{D}_{|F_{g_{r,\theta'}}|}(p)|. \quad (24)$$

To remove the constant multiplicative factor $\alpha_0^{-\frac{3}{2}}$, we normalize $|\mathcal{D}_{|F_{g_{t,\theta'}}|}(p)|$ and $|\mathcal{D}_{|F_{g_{r,\theta'}}|}(p)|$ by dividing each element of these 1D functions by $|\mathcal{D}_{|F_{g_{t,\theta'}}|}(0)|$ and $|\mathcal{D}_{|F_{g_{r,\theta'}}|}(0)|$ respectively. In other words, if we define $NFD_k(p) = \frac{|\mathcal{D}_{|F_k|}(p)|}{|\mathcal{D}_{|F_k|}(0)|}$, we obtain

$$NFD_{g_{t,\theta'}}(p) = NFD_{g_{r,\theta'}}(p), \quad (25)$$

or in general,

$$NFD_{\Re f_t(\rho,\theta)}(p) = NFD_{\Re f_r(\rho,\theta-\theta_0)}(p) \quad \forall \theta \in [0, \pi]. \quad (26)$$

In other words, after transforming an image using similarity model, a radial slice of the Radon transform of the original image corresponds to a radial slice of the Radon transform of the transformed image, if the NFD of those radial slices are equal (Figure 2). Using that information, we are able to estimate rotation, scale, and translation parameters of motion with high accuracy. The procedure of estimating motion parameters consists of five steps which are going as follows.

1. The images $\Re I_r(\rho, \theta)$ and $\Re I_t(\rho, \theta)$ are computed by applying Radon transform on reference frame $I_r(x, y)$ and target frame $I_t(x, y)$ for angles between 0° and 180° respectively.
2. Assuming that the rotational distortion is between $-\theta_{max}$ and $+\theta_{max}$, for each radial slice of $\{\Re I_r(\rho, \theta_r) | \theta_r = 70, 80, 90, 100, 110\}$, its corresponding

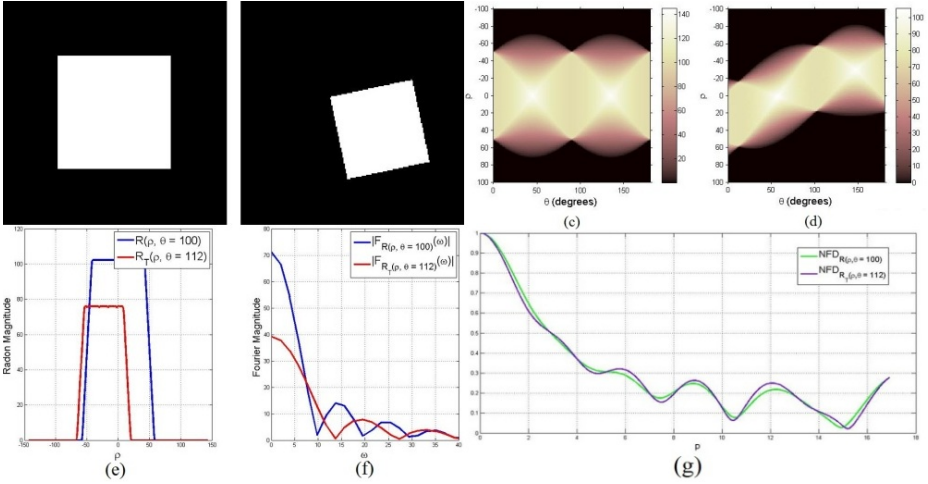


Fig. 2. Illustration of equality between NFD of the two corresponding radial slices of reference and distorted images : (a) reference image; (b) distorted image ($\alpha_0 = 4/3$, $\theta_0 = 12^\circ$, $(t_x, t_y) = (25, 15)$); (c) Radon transform of reference image; (d) Radon transform of distorted image; (e) radial slice $\Re(\rho, \theta = 100)$ of the reference image (blue color) and its corresponding radial slice $\Re_T(\rho, \theta = 112)$ of the distorted image (red color); (f) Fourier Magnitude of two corresponding radial slices; (g) NFD of two corresponding radial slices

radial slice in the range of $\{\Re I_t(\rho, \theta_t) | \theta_r - \theta_{max} \leq \theta_t \leq \theta_r + \theta_{max}\}$ is obtained using Mean Square Error (MSE) criteria. For instance, the procedure for determining the corresponding radial slice of $\Re I_t(., \theta)$ to radial slice $\Re I_r(., \theta = 70)$ is

$$\hat{\theta}_t = \underset{\theta \in [70 - \theta_{max}, 70 + \theta_{max}]}{\operatorname{argmin}} \sum_{p=0}^l (NFD_{\Re_{f_r}(\rho, \theta)}(p) - NFD_{\Re_{f_t}(\rho, \theta=70)}(p))^2, \quad (27)$$

where l is the length of 1D functions $NFD_{\Re_{f_r}(\rho, \theta)}(p)$, and $NFD_{\Re_{f_t}(\rho, \theta=70)}(p)$. After determining the pairs of corresponding radial slices, the mean of difference values $(\theta_t - \theta_r)$ is returned as estimated rotation parameter.

3. for estimating scale factor we utilize equation (22). From that equation we know that the relation between magnitude of Fourier transform of two corresponding radial slices $\Re_r(\rho, \theta - \theta_0)$ and $\Re_t(\rho, \theta)$ is

$$|F_{\Re_t}(\rho, \theta)| = \frac{1}{\alpha_0^2} |F_{\Re_r}(\frac{\rho}{\alpha_0}, \theta - \theta_0)|. \quad (28)$$

Having normalized both sides of above equation by dividing by element zero (DC component), we convert axis to logarithmic scale. Using this, scale factor is reduced to a translational displacement,

$$NFD_{\Re_t}(\log \rho, \theta) = NFD_{\Re_r}(\log \rho - \log \alpha_0, \theta - \theta_0), \quad (29)$$

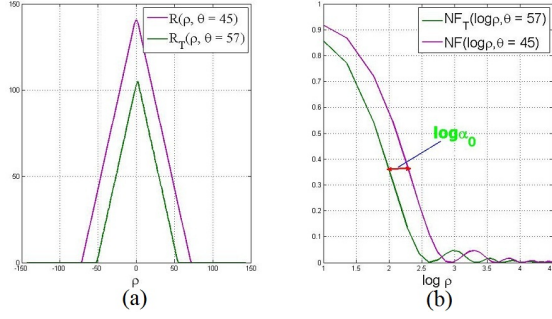


Fig. 3. estimating scale distortion (α_0) using a pair of corresponding radial slices: (a) radial slice $\Re(\rho, \theta = 45)$ of the reference image (purpel color) and its corresponding radial slice $\Re_T(\rho, \theta = 57)$ of the distorted image (green color); (b) NF of two corresponding radial slices

where $NF_{\Re}(\rho, \theta) = \frac{|F_{\Re}(\rho, \theta)|}{|F_{\Re}(0, \theta)|}$ (Figure 3). Hence, the scale factor α_0 can be found by a simple cross correlation technique. Since in step 2, we have determined the corresponding radial slices $\Re_{f_t}(\rho, \theta)$ to radial slices $\Re_{f_r}(\rho, \theta = 70, 80, 90, 100, 110)$, we estimate the scale factor using these five corresponding pairs and return the mean of these five estimations as scale distortion parameter.

4. For calculating the translation parameters, if we replace θ with $\hat{\theta} + 90$ and replace α with $\hat{\alpha}$ ($\hat{\theta}$ is estimated rotation parameter and $\hat{\alpha}$ is estimated scale factor) in Equation (18), then we have

$$\Re_{f_t}(\rho, 90 + \hat{\theta}) = \frac{1}{\hat{\alpha}} \Re_{f_r}(\hat{\alpha}\rho + t_y, 90). \quad (30)$$

Similarly, if we replace θ with $\hat{\theta}$ and $\hat{\theta} + 180$ in Equation (18), then we have

$$\Re_{f_t}(\rho, \hat{\theta}) = \frac{1}{\hat{\alpha}} \Re_{f_r}(\hat{\alpha}\rho + t_x, 0), \quad (31)$$

$$\Re_{f_t}(\rho, 180 + \hat{\theta}) = \frac{1}{\hat{\alpha}} \Re_{f_r}(\hat{\alpha}\rho - t_x, 180). \quad (32)$$

For estimating vertical displacement t_y , between reference and target frame, we choose radial slices $\Re_{f_r}(\rho, 90)$ and $\Re_{f_t}(\rho, 90 + \hat{\theta})$ and after multiplying and scaling radial slice $\Re_{f_t}(\rho, 90 + \hat{\theta})$ by $\hat{\alpha}$ and $\frac{1}{\hat{\alpha}}$ respectively, the location of the maximum cross correlation of these two radial slices is returned as vertical displacement (Figure 4).

5. In the same way, to estimate the horizontal translation parameter, if $\hat{\theta} \geq 0$ then the algorithm selects radial slices $\Re_{f_r}(\rho, 0)$ and $\Re_{f_t}(\rho, \hat{\theta})$, otherwise, the algorithm uses radial slices $\Re_{f_r}(\rho, 180)$ and $\Re_{f_t}(\rho, 180 + \hat{\theta})$ and does the same cross correlation procedure to estimate the horizontal displacement (Figure 4).

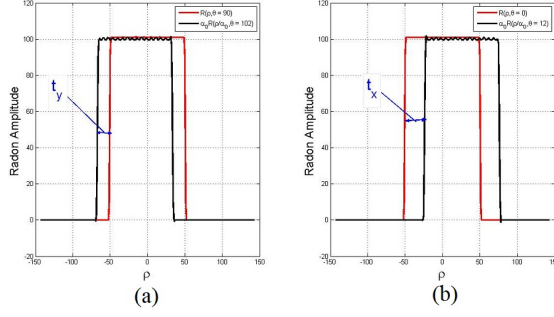


Fig. 4. estimating translational distortions (t_x, t_y): (a) estimation of vertical displacement using radial slice $\Re(\rho, \theta = 90)$ of the original image (red color) and radial slice $\Re_T(\rho, \theta = 102)$ of the distorted image (black color); (b) estimation of horizontal displacement using radial slice $\Re(\rho, \theta = 0)$ of the original image (red color) and radial slice $\Re_T(\rho, \theta = 12)$ of the distorted image (black color)

3 Experimental Results

In this section, robustness of the proposed algorithm is compared to two different methods in spatial and transform domains. We used a Sift based method [16] in spatial domain and a polar transform based method [9] in transform domain. Note that the polar transform method only estimates translational and rotational parameters of camera motion.

3.1 Experimental Setup

The proposed algorithm is tested against scale, rotational and translational distortions in some videos. We have used one synthesized video where we added random distortion to some of the frames of the video, and one real video where the distortion was due to the camera shake during capturing the video. In synthesized distortions, we have restricted the scale factor to the range of $[0.5, 1.5]$ and rotational distortion to the range of -15° to $+15^\circ$. The translational distortion is also restricted to 30 pixels in both horizontal and vertical direction. The frame resolutions of the synthesized and real sequences are 280×340 and 260×320 respectively.

3.2 Results and Discussion

Figures 5, and 7, show some frames from our test synthesized and real videos before and after stabilization. In this figures we observe that polar based method fails to estimate scale distortion for all sequences. Moreover, due to the large moving objects, the Sift results are not as accurate as our results.

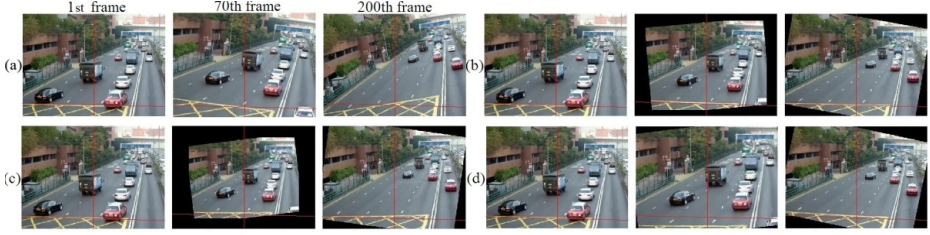


Fig. 5. Stabilization results on some frames of the test synthesized video by different methods: (a) Original frames, (b) Proposed Method, (c) Sift Method, (d) polar based method

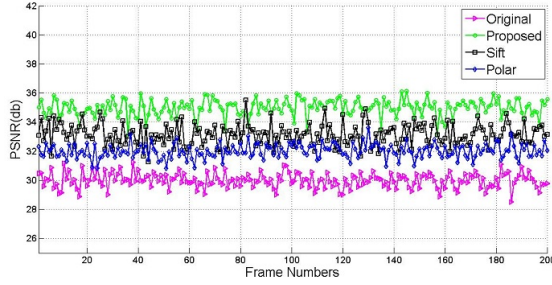


Fig. 6. The graph of PSNR according to equation 33 of the synthesized video

The fidelity of our algorithm is evaluated by the Peak Signal To Noise Ratio (PSNR) between stabilized frames which is defined as

$$PSNR(I_1, I_0) = 10 \log \frac{255^2}{MSE(I_1, I_0)}, \quad (33)$$

$$MSE(I_1, I_0) = \frac{1}{wh} \sum_{x=1}^h \sum_{y=1}^w [I_1(x, y) - I_0(x, y)]^2, \quad (34)$$

where h , and w are the height and width of the image respectively. PSNR quantifies the deviation between the stabilized frame and optimum stabilization result which can be due to various reasons such as inaccurate estimated motion, incorrect motion model, etc. The higher is the PSNR between two frames, the better is their correspondence. Figures 6, and 8, depict the PSNR curves of the sequences. It can be seen from the PSNR curves that the performance of polar transform method is poor due to the scale distortions of the some of the frames. Moreover, the performance of Sift based method is not as well as performance of our method because of existence of large moving objects in videos.

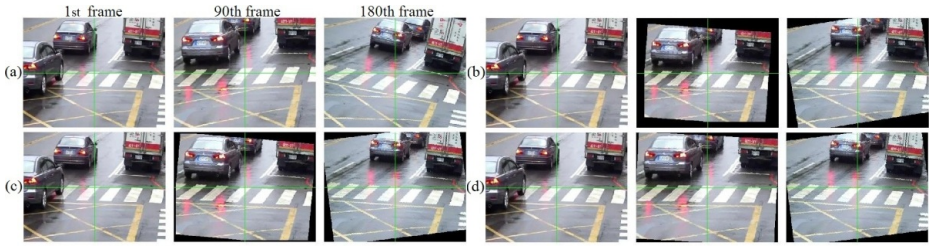


Fig. 7. Stabilization results on some frames of the real video by different methods: (a) Original frames, (b) Proposed Method, (c) Sift Method, (d) polar based method

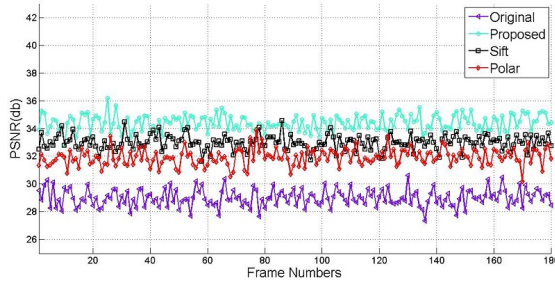


Fig. 8. The graph of PSNR according to equation 33 of the real video

4 Conclusion

In this paper, we have proposed a new transform based global motion estimation method for digital video stabilization. Our method is based on combination of Radon, Fourier and, Scale transforms which can achieve successful stabilization result in the presence of large moving objects which is a big challenge in stabilization framework. Future work will be directed to deal with more complex motion models such as affine and bilinear motion models.

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