Transformed Integral Projection Method for Global Alignment of Second Order Radially Distorted Images

Felix Albu
Dept. of Electronics
Valahia University of Targoviste
Targoviste, Romania
felix.albu@valahia.ro

Peter Corcoran
Dept. of Electronic Engineering
National University of Ireland Galway
Galway, Ireland
peter.corcoran@nuigalway.ie

Abstract—**The transformed integral projection method for image alignment of second order radially distorted images is proposed. It is shown that the proposed approach provides a better translation estimation accuracy than the integral projection method and phase correlation methods, especially for noisy distorted images.**

Keywords—Transformed integral projection method, image registration, distorted images, optical distortion

I. INTRODUCTION

Image registration is a fundamental step in many image processing applications. For example, the motion caused by hand jitter can reduce the quality of the recorded video sequences. This movement is a biological phenomenon and the effect is amplified in the small and lightweight modern cameras. To reduce the influence of the hand-jitter motion many image stabilization approaches have been proposed. The Optical Image Stabilization (OIS) has the best performance. However, OIS is an expensive solution, and it has been used on high-end digital single lens reflex cameras, video cameras, binoculars etc. The simplest approach is to use fully digital image stabilization (DIS) techniques in order to determinate the undesired image jitter and shake and compensate by digitally shifting pixel data. These methods do not need extra hardware and the power consumption can be reduced. The method presented in this paper is dedicated to cases of distorted images. These are common problems, due to cheap and faulty optics or in case of wide angle lenses. Distortion tends to be most serious in extreme wide angle, telephoto, and zoom lenses [1].

Global motion estimation has been largely used in video coding or video analysis applications. The motion between frames is estimated using the input image sequence. Then, the desired camera motion is computed. The most popular technique used for motion estimation is the block matching algorithm (BMA), in which image frames are commonly divided into non-overlapping rectangular blocks. The best match to the current block of pixels is searched for in the previous frame of the sequence within a certain search area in respect to the location of the current block. The optimal search is called the full search (FS) algorithm and searches all locations to find the best match [2]. The average magnitude distance function (AMDF) can be considered in the matching process. Basically, the vectors "slide" one over the other and the sum of the absolute difference is computed. The full search technique is very complex and the simpler but sub-optimal integral projection (IP) method [3] has been proposed. In the integral projection (IP) method, a pair of one-dimensional vectors is computed by summing the elements of each column or rows respectively. The projection vectors are correlated to find the best offset corresponding to the matched frames [3]. In [4] and [5] other IP methods and applications of them are presented. Another work that deals with different types of noise in estimating IP vectors is [6]. The more accurate but complex phase correlation (PC) method based on the phase shift theorem was also used [7]. Applying an inverse Fourier transform to the phase shift gives a delta function offset, from which the translations in the image pair is found [7]. This technique is robust, but very complex as well, because it involves the use of FFT procedure.

Most known registration methods can be applied directly on distorted images or video frames. Unfortunately, the distortions are more prominent at the corners and periphery of the image and lead to estimation errors [8]. A solution is to undistort the images using various techniques [9-12] and then apply known registration techniques. The process of removing the distortions implies the use of a grid and for each point of it a corresponding location is found in the distorted image. This implies a two dimensional sampling process and a 2-D interpolation may be used to find the color/intensity for each corresponding pixel. Typically, rational functions are found to model the distortions, especially for radial distortions models [9].

Another possibility of aligning and unwarping distorted images in which lens profiles for a variety of lens and camera combinations are pre-computed is described in [9]. Metadata stored with images are used and the initial unwarping function is applied to the coordinates of feature points of the component images to generate substantially rectilinear feature points, which are used to estimate focal lengths, centers, and relative rotations for pairs of the images [9]. A global nonlinear optimization is then applied to the initial unwarping functions. However, the alignment methods based on feature points are still too complicate to implement in a practical real-time imaging system [9], [12]. There are several methods that can be used to find the distortion function parameters of the images [1, 13-15].

In this paper, we propose to estimate the translations between distorted images using the Transformed Integral Projection (TIP) method *directly on the distorted images or video frames*. The problem of estimating the motion in 2-d images is converted to that of *nonlinear warping* between 1-d curves.

Simulation results demonstrate the superiority of the proposed algorithm over conventional integral projection and phase compensation methods. The transformed integral projection method computes the translations between two second order radially distorted images by transforming the integral projection vectors unlike the IP vector method of [3]. In addition, the robustness to noise of IP or PC methods for distorted images is not considered in previous publications.

This paper is organized as follows: Section II describes the transformed integral projection method (TIP). In the Simulation section the performance of the TIP method is compared with that of integral projection for various noise types. Finally a summary of our contribution concludes the paper.

II. TRANSFORMED INTEGRAL PROJECTION METHOD

The integral projection method is not very precise in the case of distorted images. In Fig. 1 there are six images: the central ones are the original images, while the left images are the barrel distorted images and the right images are the pincushion deformed images. The upper part of the Fig. 1 shows grid images, while the bottom part shows the Lena images.

The function that models the deformed images from Fig. 1 is

$$F(r,k) = 1 + kr^2 \tag{1}$$

where r, called radius is the distance from the centre of the image and k is a determined constant which has a positive value for barrel images and a negative value for the pin-cushion distorted images.

Barrel distortion is found in wide-angle views and it is the result of the squeeze that is applied in order to fit the image in a smaller space [13]. The pin-cushion distortion is found in telephoto because of the stretching applied in the image in order to fit the space. These distortions are visually most prominent at the image corners and sides [13]. In order to see the effect of the distortions on the integral projection vectors the barrel distorted grid image with k = 0.3 and the pin-cushion grid image with k = - 0.3 are used. The integral projection vectors are shown on Fig.2. It can be easily seen on this simple example that the projection vectors of the barrel and pincushion images are deformed starting from the centre towards the extremities of the images. The edges that could easily help to detect the horizontal displacement through the integral projection vectors are attenuated a lot and therefore, estimation errors are expected. Typically, the estimated displacements using the IP method tend to be higher in case of pin-cushion distorted images and lower on barrel distorted images.

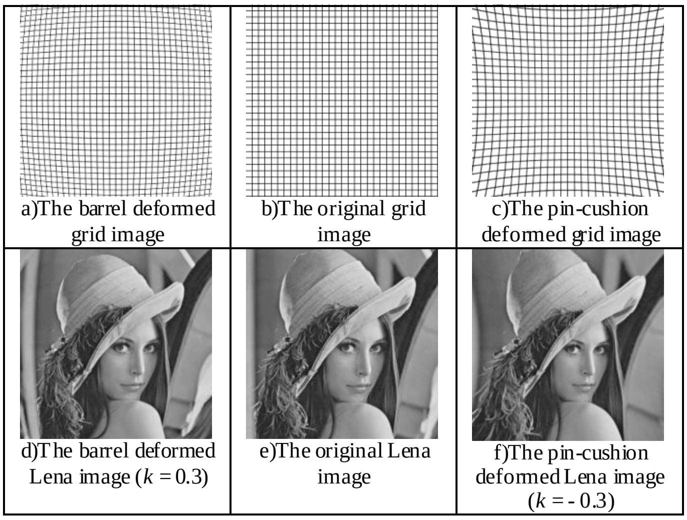

Fig. 1 a) The barrel deformed grid image; b) The original grid image; c) The pin-cushion distorted grid image; d) The barrel deformed Lena image; e) The original Lena image; f) The pin-cushion distorted Lena image;

The undistorted coordinates are given by the formula [16]:

$$\begin{aligned} x_u &= x_d\left(1 + kr_d^2\right) \\ y_u &= y_d\left(1 + kr_d^2\right) \end{aligned} \tag{2}$$

The inverse distortion model is obtained by solving the equation [16]

$$r_u = r_d\left(1 + r_d^2\right) \tag{3}$$

where $r_d^2 = \sqrt{x_d^2 + y_d^2}$ is the distorted radius and $r_u^2 = \sqrt{x_u^2 + y_u^2}$ is the undistorted radius. A third degree polynomial is solved [16] and the distorted coordinates are given by

$$\begin{aligned} x_d &= x_u r_d / r_u \\ y_d &= y_u r_d / r_u \end{aligned} \tag{4}$$

The scheme of the proposed method is shown in Fig. 3. The main idea of the TIP method is to approximate the projection on the axis of an approximation of the inverse function ($F^{-1}(r,k)$). It corresponds to the dotted part from Fig. 3. It is assumed that the function that models the distortion of the original image, $F(r,k)$, is known. The TIP method reduces to the standard IP method without the dotted part from Fig. 3. The TIP vectors are obtained by applying the method from [16] to the particular case of one-dimensional IP vectors. Of course the accuracy of the inverse function estimation plays an important role for the precision of the proposed method. Therefore, a one dimensional projection vector is used as an input to the above model particularized for one dimension. The method is not only limited for images that exhibit second order radial distortions (barrel and pincushion distortions).

It was shown in [17-19] that more complicated distorted models with more even powers of the distortion radius can be well approximated with only the first order radial symmetric distortion parameter. The proposed scheme can be used for many other possible distortions [20].

The TIP method complexity is higher than that of IP method, because it implies nonlinear operations on the sum of pixels for image columns or rows.

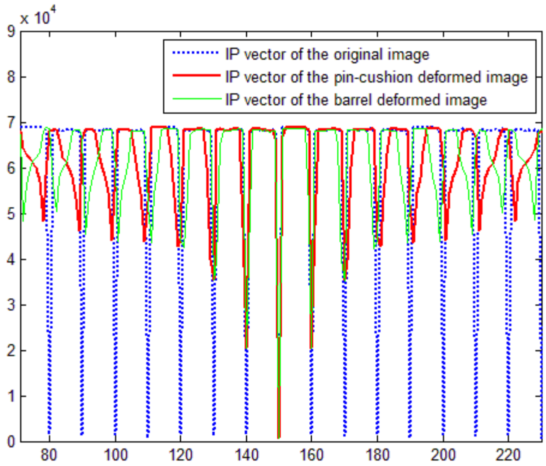

Fig. 2 The IP vectors of the grid images from Fig. 1.

However, it does not involve known complex distortion image correction or the Radon transform [21-22].

The unwarping process can still render an image with little radial distortion [9], therefore TIP method provides an advantage over correcting for geometric distortion before alignment. It is obvious that TIP reduces to IP when there is no distortion, i.e. k = 0. Also, the TIP vectors have a different length than the IP vectors (higher length for pin-cushion images and lower length for barrel images).

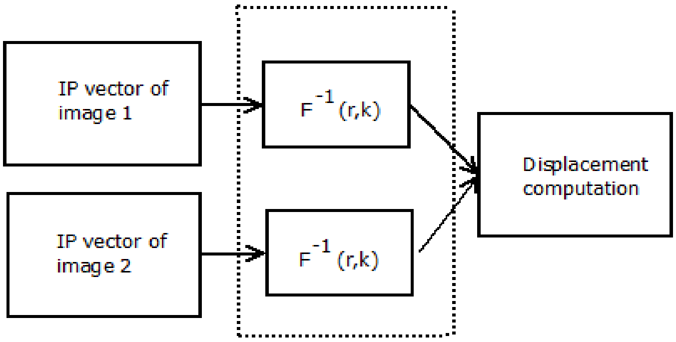

Fig. 3 The proposed scheme for displacement estimations

In Fig. 4a the central part of the vertical IP projection vectors of two translated pin-cushion distorted "Lena" images are plotted (k = - 0.3). The original undistorted images were translated with 15 pixels vertically. Figure 4b shows the vertical TIP vectors. It can be noticed from Fig. 4 that the considered TIP vectors have different length and shape than the IP vectors.

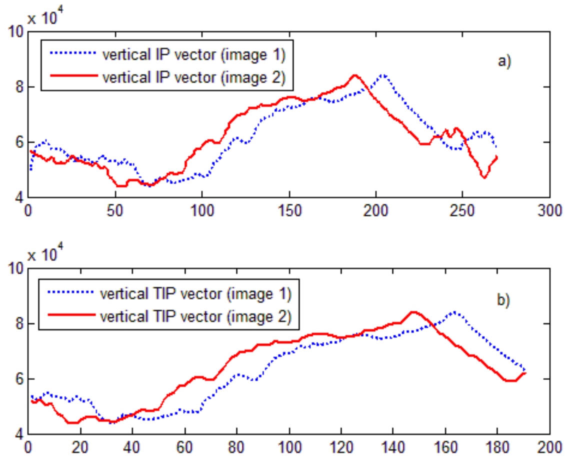

Fig. 4 a) The vertical IP vectors of the images; b) The vertical TIP vectors of the images.

For the specific case of the previous figure, the TIP method finds the exact vertical displacement of 15 pixels, while the IP methods find a displacement of 16 pixels.

III. SIMULATION RESULTS

We examine the robustness of the proposed method by simulations using Lena images with different displacement values, in the noise-less case and two noise types. The horizontal and vertical displacements are individually varied from 1 to 20 pixels on distorted images (pincushion (k = - 0.3) and barrel distortions (k = 0.3)).

The sum of absolute displacement errors between the exact displacements and the estimated ones using the IP and TIP methods is computed. In the noise-less case the results are plotted in Fig. 5.

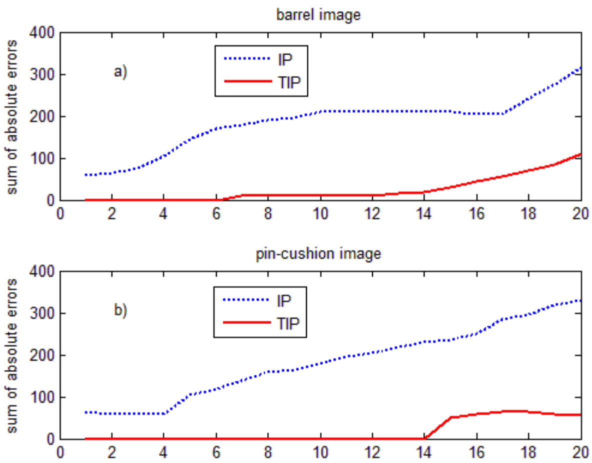

Fig. 5 Sum of absolute errors for distorted images in the noise-less case; a) barrel image; b) pin-cushion image

It can be seen that the TIP method obtains a better approximation of the displacement values for both types of distortions. Also, the accuracy of TIP method it is better for the pin-cushion image that for the barrel image.

Figure 6 shows the sum of absolute displacement errors for distorted Lena images with several k values around the exact value of k = - 0.3. The distorted pin-cushion images with k = - 0.3 were used but errors regarding the estimation of k value of $F(r)$ were assumed.

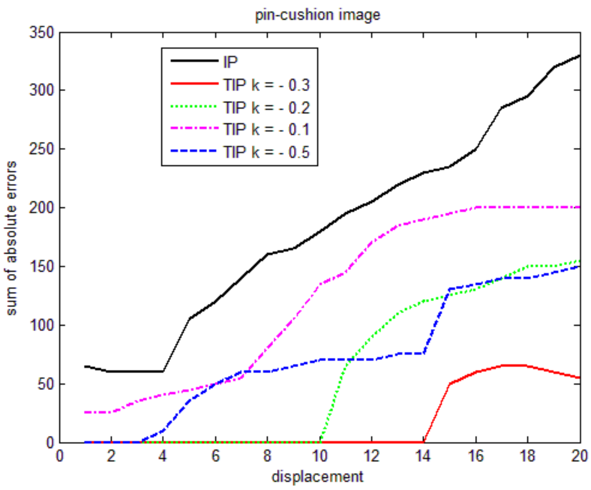

Fig. 6 Sum of absolute errors for different k values in case of the pin-cushion image.

The best TIP estimation accuracy over IP and PC was obtained for the speckle noise on pin-cushion images (only 3% and 2% respectively). As expected, the best results are obtained when TIP uses the exact k = -0.3 value. Also, it can be seen that worse results are obtained if the distortion coefficient is farther from the exact one, but they are still better than those of the IP method. The TIP method obtains better results than IP method even if the distortion coefficient k is not the right one.

Therefore, there is not a strict requirement of an exact modeling of $F(r)$. The TIP method has a great tolerance to coefficient estimation error for the investigated image distortions. Even for these cases the TIP method has a better accuracy than IP method.

We examined the robustness of the IP, PC and TIP methods in case of the Gaussian noise (Fig. 7), Speckle noise and Salt & pepper noise. The noise was generated with the Matlab *imnoise* function and the errors from 10 trials are counted.

The same conclusions about TIP as those obtained for the noise-less case can be obtained from Fig. 7. It is obvious that the TIP method has the best robustness to Gaussian noise in comparison with the IP or PC methods on distorted images. In case of barrel images, the total sum of estimation errors of the TIP method is only about 10% of the IP and 16% of PC. The corresponding percentages for the pin-cushion images are 8% and 4% respectively. The same results were obtained for other types of noise such us speckle noise (Fig. 8, the case of zero mean and variance = 0.02) or salt & pepper noise (Fig. 9, the case of noise density = 0.02).

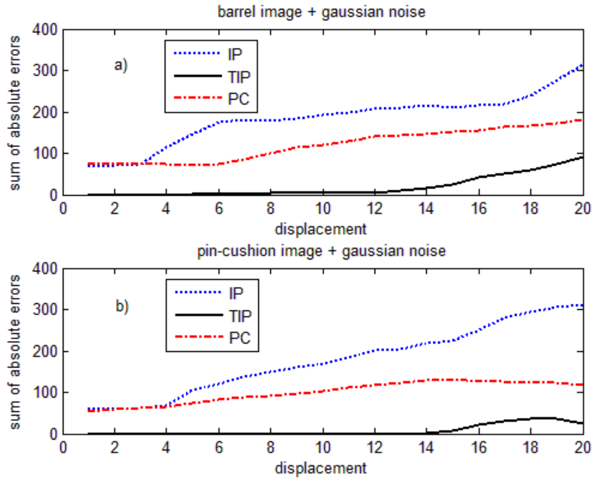

Fig. 7 Sum of absolute errors for distorted images contaminated with Gaussian noise: a) barrel image; b) pin-cushion image

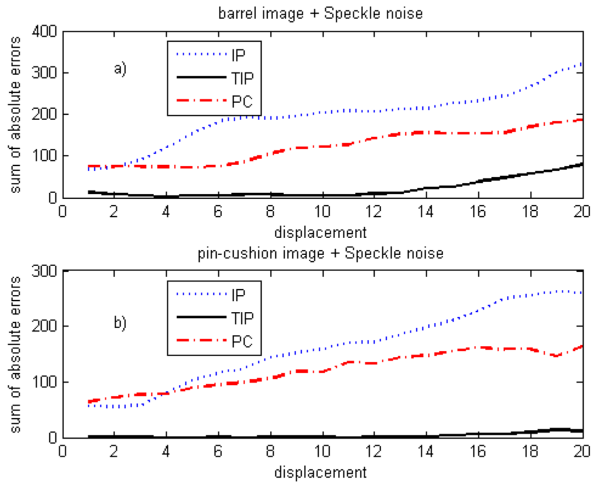

Fig. 8 Sum of absolute errors for distorted images contaminated with Speckle noise: a) barrel image; b) pin-cushion image

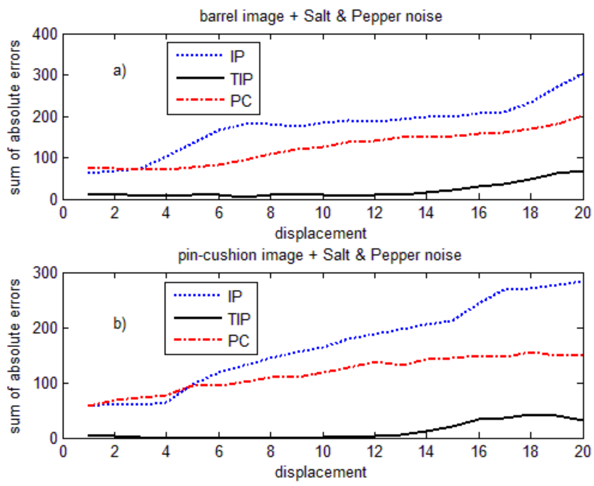

Fig. 9 Sum of absolute errors for distorted images contaminated with Salt & pepper noise: a) barrel image; b) pin-cushion image

Figure 10 shows the sum of absolute displacement errors for distorted Lena images with several *k* values around the exact value of *k* = - 0.3 for the case of Gaussian noise with zero mean and variance = 0.003. Therefore, similar results were obtained for inexact distortion models. For the investigated case, the sum of absolute errors of TIP in case of noisy images is increasing, but still better than that of IP and PC methods. It can be seen from Fig. 10 that TIP with inexact parameters (e.g. -0.1 or -0.3) achieves better accuracy than PC for displacement values smaller than 12.

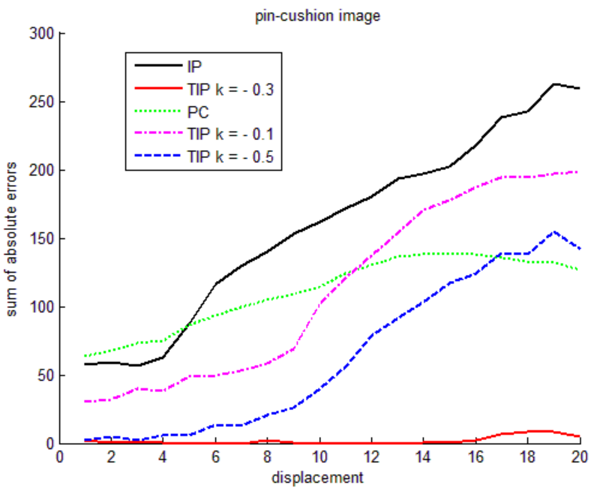

Fig. 10 Sum of absolute errors for different *k* values in case of the pin-cushion image contaminated with Gaussian noise.

Our simulations confirmed that the accuracy of the TIP method depends on the displacement size, type of distortion, type of the noise and image content.

The TIP method performs better than IP for distorted images especially for high translation values. However, the advantages of TIP over IP are reduced for small distortions.

We verified the performance on a video stabilization application with short videos with a pin-cushion distortion with an estimated *k* = -0.01. The quality of video stabilization is measured by using the error metric called ITF (Interframe Transformation Fidelity) [23]. The gain of the ITF measure of stabilized video using TIP over that using IP is about 0.5 dB.

Our future work will be focused in investigating this method on wider test cases and other types of distortions. Known techniques for rotation estimation, scale factor estimations between two images can be applied on these TIP vectors too [8], [24-25]. The camera calibration techniques (e.g. [16-18]) could be combined with the proposed method. Also, we intend to compare the TIP method with other registration techniques (e.g. [26-28]) and investigate the reduction of its numerical complexity.

IV. Conclusions

The transformed projection vector method was proposed for global translation estimation of the distorted images or video frames. It is shown that the TIP method obtains better translation estimations than the IP method for barrel or pin-cushion images even for less accurate distortion coefficient estimations. Also, it was shown that the TIP method has a greatly improved robustness to various noise types over the IP or PC methods.

Acknowledgment

This work was supported by UEFISCDI Romania under Grant PN-IIPT-PCCA-2011-3.2-1162.

References

[1] Imatest software, http://www.imatest.com/docs/distortion/

[2] J. Feng, K.-T. Lo, H. Mehrpour, and A. E. Karbowiak, “Adaptive block matching motion estimation algorithm using bit plane matching,” in Proc. of ICIP 1995, pp. 496–499, 1995.

[3] K. Sauer and B. Schwartz, "Efficient Block Motion Estimation Using Integral Projections", IEEE Trans. Circuits, Systems for video Tech., vol. 6, No. 5, pp. 513-518, October 1996.

[4] F. Albu, C. Florea, A. Zamfir, and A. Drimbarean, “Low Complexity Global Motion Estimation Techniques for Image Stabilization”, in Proc. of ICCE 2008, Las Vegas, USA, pp. 465-467, January 2008.

[5] F. Albu, D. Hagiescu and M. Puica, “Quality evaluation approaches of the first grade children’s handwriting”, in Proceedings of the 10th International Scientific Conference on eLearning and software for Education, pp. 17-23, 2014.

[6] S.C. Cain, M.M. Hayat, and E.E. Armstrong, “Projection-based image registration in the presence of fixed-pattern noise”, IEEE Transactions on Image Processing 10, pp. 1860–1872, 2001.

[7] C.D. Kuglin and D.C. Hines “The phase correlation image alignment method”, in Proc. Int. Conf. Cybernetics and Society, pp. 163-165, Sept. 1975.

[8] F. Albu, “Registration of distorted images”, US 13/234139, September 15, 2011.

[9] H. Jin, “Metadata-driven method and apparatus for automatically aligning distorted images”, US 8,368,773, February 2013.

[10] J. Mallon and P. F. Whelan, “Precise radial un-distortion of images”, Proc. of. ICPR 2004, vol. 1, pp. 18-21, 2004

[11] B. Zitová and J. Flusser, “Image registration methods: A survey,” Image Vis. Comput., vol. 21, pp. 977–1000, 2003.

[12] L. Romero and C. Gomez, “Correcting Radial Distortion of Cameras with Wide Angle Lens Using Point Correspondences, Scene Reconstruction Pose Estimation and Tracking, Rustam Stolkin (Ed.), InTech, 2007

[13] A. Bismpigiannis, “Measurements and correction of geometric distortion”, http://scien.stanford.edu/pages/labsite/2007/psych221/projects/07/geometric_distortion/geometric_distortion_project.pdf, Stanford, 2007.

[14] A. Das and D. Patil, “Efficient Measurement and Correction Techniques for Lens Distortion”, http://scien.stanford.edu/pages/labsite/2006/psych221/projects/06/ddpatil/ee362ProjectReport.pdf, Stanford, 2006.

[15] H. Ojanen, “Automatic Correction of Lens Distortion by Using Digital Image Processing”, http://www.math.rutgers.edu/~ojanen/undistort/undistort.pdf, 1999.

[16] F. Devernay and O.D. Faugeras, “Automatic calibration and removal of distortion from scenes of structured environments”, The International Society for Optimal Engineering, SPIE, Vol. 2567, San Diego, CA, 1995.

[17] H. A. Beyer, “Accurate calibration of CCD-cameras”, in Proceedings of the International Conference on Computer Vision and Pattern Recognition, Urbana Champaign, IL, June 1992.

[18] R. Y. Tsai, “A versatile camera calibration technique for high-accuracy 3D machine vision metrology using off-the-shelf TV cameras and lenses”, IEEE Journal of Robotics and Automation, vol. 3, No. 4, pp. 323–344, August 1987.

[19] O. Faugeras and G. Toscani, "Structure from Motion using the Reconstruction and Reprojection Technique", in Proc. of IEEE Workshop on Computer Vision, pages 345–348, November-December 1987.

[20] L. Ma, Y. Chen, and K.L. Moore, "Rational radial distortion models of camera lenses with analytical solution for distortion correction", International Journal of Information Acquisition, 01, no. 2, pp. 135-147, 2004.

[21] F.Hjouj and D. W. Kammler, "Identification of Reflected, Scaled, Translated, and Rotated Objects from their Radon Projections", IEEE Transactions on Image Processing, vol. 17, no. 3, pp. 301-310, March 2008.

[22] G. Chen, and S. Coulombe, "A new image registration method robust to noise", Multidimensional System and Signal Processing Journal, vol. 25, no 3, pp. 601-609, Mar. 2014.

[23] L. Mercenaro, G. Vernazza, and C. Regazzoni, "Image stabilization algorithms for video-surveillance application," Proceedings of International Conference on Image Processing (ICIP), pp. 629–632, 2001.

[24] F. Albu, "Registration of differently scaled images", US 13/234,146, September 15, 2011.

[25] F. Albu, L. Murray, P. Stec and I. Raducan, "Fast rotation estimation of objects in sequences of acquired digital images", US 8,587,665, November 19, 2013.

[26] S. Kumar, H. Azartash, M. Biswas and T. Nguyen, "Real-Time Affine Global Motion Estimation Using Phase Correlation and its Application for Digital Image Stabilization", IEEE Transactions on Image Processing, vol. 20, no. 12, pp. 3406-3418, 2011.

[27] Y.G. Ryu and M.J. Chung, "Robust Online Digital Image Stabilization Based on Point-Feature Trajectory Without Accumulative Global Motion Estimation", IEEE Signal Processing Letters, vol. 19, no. 4, pp. 223-226, 2012.

[28] M. Okade and P.K. Biswas "Video stabilization using maximally stable extremal region features", Multimedia Tools and Applications, vol. 68, pp. 947-968, 2014.