IMAGE SEQUENCE STABILIZATION USING FUZZY KALMAN FILTERING AND LOG-POLAR TRANSFORMATION

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Abstract: Digital image stabilization (DIS) is the process that compensates the undesired fluctuations of a frame's position in an image sequence by means of digital image processing techniques. DIS techniques usually comprise two successive units. The first one estimates the motion and the successive one compensates it. In this paper, a novel digital image stabilization technique is proposed, which is featured with a fuzzy Kalman estimation of the global motion vector in the log-polar plane. The global motion vector is extracted using four local motion vectors computed on respective sub-images in the log-polar plane. The proposed technique exploits both the advantages of the fuzzy Kalman system and the log-polar plane. The compensation is based on the motion estimation in the log-polar domain, filtered by the fuzzy Kalman system. The described technique outperforms in terms of response times, the output quality and the level of compensation.

1 INTRODUCTION

Digital stabilization aims at preserving the intentional camera movements, while it smoothes the video output from unwanted oscillations. Almost any acquired image sequence is affected by noise and undesired camera jitters. Depending on the application those unwanted fluctuations are caused by a rough terrain, the shaking of the hand carrying the camera etc. Image stabilization is a necessity, as vision plays a key role to many applications and, therefore, the output of the image sequence should be free from noise, and should be smooth enough so that useful results to be extracted. Image stabilization is application depended. In the case of a camera mounted on an active servo mechanism, the undesired oscillations are mostly the rotational ones and the stabilization is implemented by servo motors, which compensate the pan and the tilt camera movement, respectively. This technique is known as optical stabilization (Sato et al., 1993). In case that electronic hardware is utilized to compensate the sensed camera moves the stabilization is referred as electronic (Morimoto and Chellappa, 1996). Finally, when only pure image processing techniques are adopted then it is known as digital image stabilization. This is the process of preserving the intended camera motion, while removing the unwanted noise and motion effects with the utilization of digital image processing (Ko et al., 1998). DIS has been applied to many applications, either real-time or non real-time.

A DIS system is composed by two successive units: the motion estimation and the motion compensation one. The first unit aims at the computation of the global motion vector. The estimation phase is being followed by the compensation processing unit. The produced compensation vector finally shifts the current frame to acquire an image sequence, which is free from irregularities, keeping only the desired global motion. There is a wide use of fuzzy logic in image processing applications (Chanon et al., 2002). In case of non-linear and ambiguous applications fuzzy logic is probably the finest solution.

Various techniques have been developed for the global motion vector calculation, such as phase correlation matching (Kwon et al., 2005) or

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normalized cross correlation (Hsu et al., 2005). A real-time implementation that adopts the two images' matching through the Fourier-Mellin transformation has been reported in (Martinez et al., 2004). The use of fuzzy logic for the global motion vector computation can produce optimal results (Güllü and Ertürk, 2004). In order to enhance the compensated frame position Kalman filtering was utilized (Hsu et al., 2005, Ertürk, 2002). The estimation of the motion in a sequence is also realized by optical flow techniques. The approximation of the image flow field provides both the translational and rotational information. The undesired motion effects are calculated in (Suk et al., 2005) by estimating the rotational center and the angular frequency from the local translational motion definition by fine-to-coarse multi-resolution motion estimation. In (Pauwels et al., 2007) the stabilization is accomplished by fixating at the central image region, whilst optical flow estimation optimizes this approximation. In most of the cases the global motion vector is computed via a series of local motion vectors. These describe the movement in a particle of the image, which results to a better estimation of the indented camera movement and the undesired motion.

In this paper, a novel fuzzy Kalman digital image stabilization technique in the log-polar plane is proposed. First a transformation from the Cartesian plane to the log-polar one takes place. The acquired log-polar image sequence provides lesser information in the background of the scenery than in the foreground. This is due to the proper attribute of the log-polar transformation to preserve high-resolution at the center of the image, which diminishes logarithmiticaly towards the periphery. The motion estimation in the log-polar plane provides a space-variant distribution of the local motion vectors due to the aforementioned nature of the log-polar plane. Consequently, the extracted local motion vectors are imported into a recursive fuzzy system based to the one presented in (Güllü and Ertürk, 2004). However there are some distinct differences. One lies to the fact that in this paper, the fuzzy system utilizes the Kalman filter's mathematical model to filter the inputs straightforwardly. Moreover, no mean operation filtering takes place to the measured fluctuations. Finally, the filtered vectors, define the global motion vector from which the compensation vector is calculated. The innovation of using log-polar images for the motion field extraction provided optimal results not only to the stabilization of each frame, but also to the visual quality of the video output. The advantages of the log-polar plane are well exploited, as (i) the processing time is lesser, (ii) a single motion estimation extraction provides information for both the rotational and translational irregularities and (iii) the center of attention has a higher impact to the whole process without further preprocessing.

2 LOG-POLAR TRANSFORMATION

The motion estimation process preserves high computational burden, so it is normally improper for real-time applications. One way to overcome the computational burden is to sub-sample the images. Yet, to estimate the motion field, all available information is needed. Thus, a resolution decrease is inappropriate as it causes loss of major information and the provided results are sparse and inaccurate. However, the volume of the image data can be reduced by a topological arrangement, without loss of information. Notably, a space-variant arrangement such as log-polar provides lesser image data without constraining the field of view, or the image resolution at the fixation point. The log-polar transformation is based on the human's eyes projections of the retina plane to the visual cortex. It finds its origins into studies on the vision mechanisms of the primates. The adoption of this topology into artificial vision systems exhibits several advantages as in visual attention, throughput rate and real-time processing. Many applications of the log-polar transformation have been reported, such as the time-to-impact estimation (Tistarelli and Sandini, 1993), wavelet extraction based on log-polar mapping (Pun and Lee, 2003), tracking (Metta et al., 2004) and disparity estimation and vergence control in (Manzotti et al., 2001).

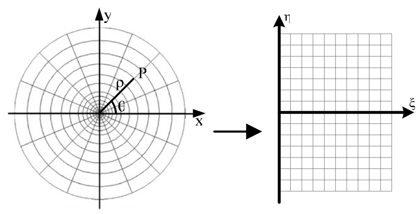


Figure 1: The log-polar transformation maps radial lines and concentric circles into lines parallel to the coordinate axes.

The mathematical model of the log-polar mapping can be expressed as a transformation between the polar plane (ρ, θ) (retinal plane), the log-polar plane (η, ξ) (cortical plane) and the Cartesian plane (x, y) (image plane).

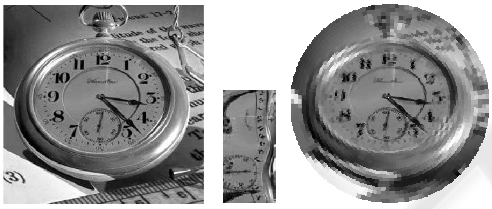
Assuming that *Nr* is the number of cells in the radial direction and Na is the number of cells in the angular direction the mapping from the polar coordinates (ρ, θ) to the log-polar ones (η, ξ) is defined as:

$$\xi = \log_a\left(\frac{\rho}{\rho_0}\right) \tag{1}$$

$$\gamma = \frac{N_\alpha}{2\pi}\eta \tag{2}$$

where ξ counts the rows, γ the column and ρ_0 is the radius of the fovea circle. The logarithmic basis α is obtained from the foveal radius, the image radius $\rho_{\max}$ and the radial resolution *Nr*.

$$\alpha^{N_r} = \frac{\rho_{\max}}{\rho_0} \text{ or } \alpha = e^{\frac{1}{N_r}\ln\left(\frac{\rho_{\max}}{\rho_0}\right)} \tag{3}$$



(a) (b) (c)

Figure 2: (a) Cartesian image; (b) log-polar image and (c) reconstructed Cartesian from log-polar image.

3 ESTIMATION OF THE MOTION

The proposed system intents to produce stabilization control signals from an image sequence by digital image processing in the log-polar plane. Independently of the adopted technique for the motion estimation, the whole process has shown robustness and the output video had been compensated in a way that the visual quality to be as smooth as possible.

To test the proposed concept two different motion estimation techniques were implemented: a differential optical flow method, from where the two dimensional image displacements are extracted, and a block matching algorithm (Mahmoud et al., 2006). The measures from the block-matching algorithm are accurate enough, despite the erroneous flow values introduced in polar deformation, due to the fictitious gray-value curvature in the polar image (Daniilidis and Krüger, 1995). In order to attenuate the aliasing effects and to reduce the error in the computation of the spatial gradient appropriate filtering is needed. Notwithstanding, a full-search frame matching is robust enough but suffers from high computational cost even when the amount of information has already been reduced due to the log-polar transformation. On the other hand, the optical flow technique provided shorter processing time and it was finally selected for the system implementation.

The global motion estimation vector is fed to the proposed fuzzy Kalman system. This accomplishes the operation of the motion estimation filtering from which the compensation vector is extracted. The compensation unit processes the provided information of the estimation unit and produces the final stabilized video. The block diagram of the proposed system is shown in the Figure 3.

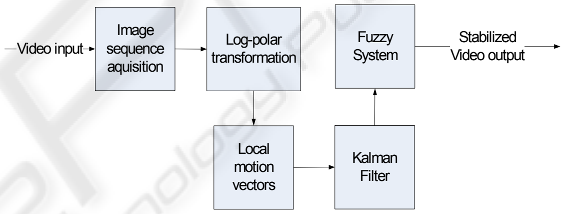


Figure 3: The block diagram of the proposed system.

3.1 Optical Flow and Image Translation

The image motion is basically the three dimension motion projection of the real world onto the two-dimensional image plane. This is expressed as either image velocities or image displacements in the x and y axes. These vectors comprise the optical flow field. Optical flow techniques are widely used in many applications and calculating approaches and are divided in three main categories: the differential techniques, the frequency based ones and the matching methods (Barron et al., 1997). The implemented calculation method is a differential one. The image velocity is computed from spatiotemporal derivatives of the image intensities assuming continuity to the image domain.

The Horn and Schunk optical flow technique, which was implemented in this paper, combines the gradient constraint with a global smoothness factor in order to constraint also the optical flow field v(x,*t*)=(*u*(x,*t*),*v*(x,*t*)), which by minimization gives:

$$\int_D (\nabla I \cdot \mathrm{v})^2 + \lambda^2(\|\nabla u\|_2^2 + \|\nabla v\|_2^2)\,d\mathrm{x} \tag{4}$$

where D is the domain in which the equation is defined, and the magnitude of λ influences the smoothness factor.

By solving iteratively a new set of velocities is computed from the derivatives and the average of the previous velocities. The velocities equations obtained are:

$$u^{k-1} = \bar{u}^{k} - \frac{I_x[I_x \bar{u}^{k} + I_y \bar{u}^{k} + I_t]}{a^2 + I_x^2 + I_y^2} \tag{5}$$

and

$$v^{k-1} = \bar{v}^{k} - \frac{I_y[I_x \bar{v}^{k} + I_y \bar{v}^{k} + I_t]}{a^2 + I_x^2 + I_y^2} \tag{6}$$

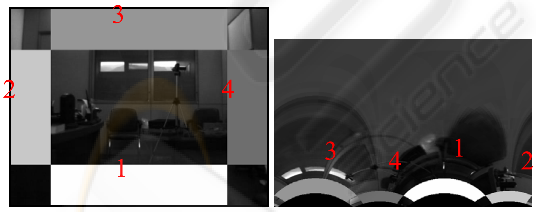
where k denotes the iteration number, which by experiments was set to 25, as it provided better results.

The initial velocities u^0, v^0 are set to zero. The local averages $\bar{u}^{k}$ and $\bar{v}^{k}$ are defined as a 3×3 distance weighted Laplacian mask.

$$\bar{u}^{k} = u^{k}\begin{bmatrix} 1/12 & 1/6 & 1/12 \\ 1/6 & -1 & 1/6 \\ 1/12 & 1/6 & 1/12 \end{bmatrix} \tag{7}$$

and

$$\bar{v}^{k} = v^{k}\begin{bmatrix} 1/12 & 1/6 & 1/12 \\ 1/6 & -1 & 1/6 \\ 1/12 & 1/6 & 1/12 \end{bmatrix} \tag{8}$$

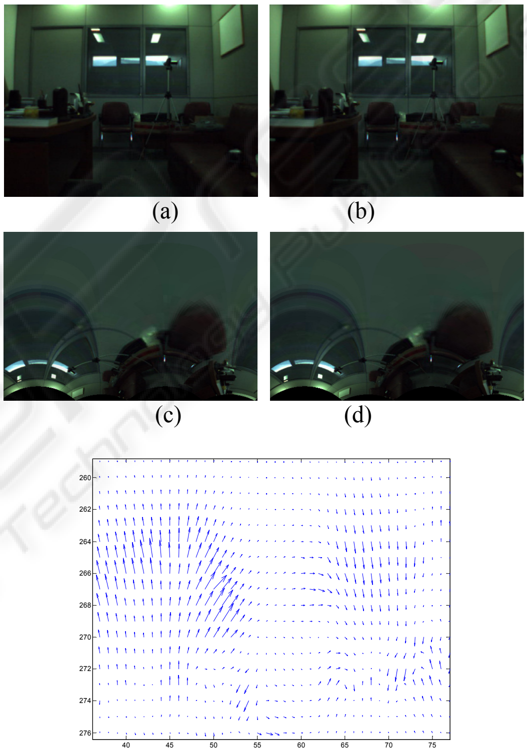


(a) (b)

Figure 4: The selected sub-images for motion estimation, in the (a) Cartesian and (b) log-polar plane, respectively.

The horizontal and vertical axes displacements were initially extracted from selected image regions. These have a rectangular shape of 440×100 pixels along the x axis, whist the dimensions along the y axis are 100×280 pixels, respectively (Figure 4.(a)). The local motion vectors were calculated from the respective sub-images at the log-polar plane (Figure 4(b)).

Yet, the motion estimation in the log-polar plane has some special features that should be taken into consideration, i.e. the motion vectors are not transferred straightforwardly from the Cartesian to the log-polar plane. The final motion estimation vectors, where computed according to the foretold considerations, in order to obtain the global motion vector. The displacements are straightly imported to the fuzzy Kalman system without any other processing, such as mean filtering or median values extraction. However, the high number of iterations during the optical flow technique implementation provided as optimal results as possible.



(e)

Figure 5: The optical flow field of two successive images¨ (a) the first frame, (b) is the successive one, (c) the log-polar transformation of the first frame, (d) the log-polar transformation of the second one and (e) the optical flow, estimated on the log-polar plane.

3.2 Motion Estimation Phase

Another critical issue is the noise factor, which needs to be filtered. The noise is divided into the measurement and the process noise, which are the error during the variables calculation and the error during the whole process, respectively. These perturb the estimation of the image motion field, and are present during the global motion vector estimation. The fuzzy system operates as a recursive filter, since its inputs stem from the Kalman filter. Two phases occur: the estimation and the correction one. The recursiveness lies on the fact that an a priori estimation is calculated and is being corrected by an a posteriori estimation. The Kalman filter's rules are illustrated in (Welch and Bishop, 2001). The adopted rules from the Kalman filter to the fuzzy system result in a fuzzy Kalman filtering system.

The distributed fuzzy Kalman system has two inputs. The first one is the filtered value in the current time interval, whilst the second one is the measured value from the previous time interval. The estimation equations can be defined as:

$$Input1 = z_k - \hat{x}_{k-1} \tag{9}$$

$$Input2 = Input1_k - Input1_{k-1} \tag{10}$$

whilst the correction ones as:

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k) \tag{11}$$

where k is the time index, $\hat{x}_k$ is the a posteriori estimate of x and z_k denotes the measurement in the k time index.

The image translation results, exported from the optical flow, are imported into the proposed fuzzy Kalman system. The system has two inputs, one for the current time index and one for the previous time index, described by (9) and (10). The fuzzy membership functions for the first input's displacements are called *negative big*, *negative*, *zero*, *positive* and *positive big*, whilst the same rules define the second input's displacements. Although the complexity of the problem is quite high, the five membership functions are sufficient to grant optimal results. The final utilization of the membership function is illustrated in Figure 6.

Although the rule set is composed of 25 *if-then* rules, the response time of the filter was quick and accurate. Experiments were made introducing two more membership functions for each input and output. The effort was focused to cover in a higher level the step between the positive and negative big with the positive and negative membership functions, respectively. The final output showed that there is a boundary for the accuracy in terms of complexity, i.e. the higher the complexity, the higher the accuracy. Still, the same relationship stands for the response time. Thus, there is a trade-off between time and accuracy.

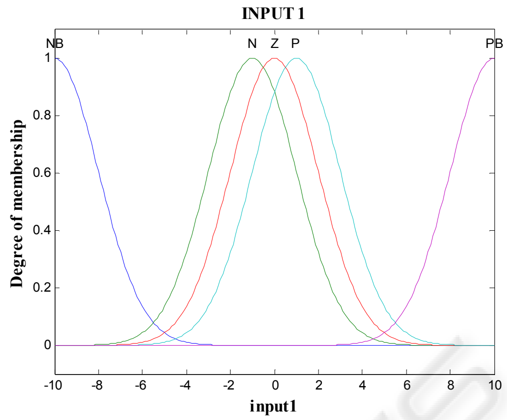


Figure 6: The membership functions of the fuzzy Kalman filter.

Furthermore, experiments were made for the computation of the compensation motion vector. Initially, the output of the fuzzy Kalman system was directly utilized for the compensation vector. In addition, a median filtering was implemented to the output values of the fuzzy system. However, the compensation vector, which exhibited optimal results is defined as:

$$\begin{aligned} CMV(t) &= k(CMV(t-1)) \\ &+ (aGMV(t)) + (1-a)GMV(t-1)) \end{aligned} \tag{12}$$

where t represents the frame number, $0 \leq a \leq 1$ and k is a factor for determining the weight between current frame stabilization and indented camera movement. Finally, frame shifting is applied when both horizontal and vertical CMVs are specified.

4 EXPERIMENTAL RESULTS

Image sequences were captured with an active stereo vision head. Some of the testing input videos were acquired during an optical stabilization operation of the head's servo motors. All of these sequences suffer from high frequency image jitters, produced intentionally by the user for testing. They also suffer from high illumination changes as well as from fluctuations caused by the servo motors. Further experiments were made, capturing video on a free course. These sequences suffer from motion blurred frames. The remedy to such sequences is a higher frame rate. As the acquired videos were tuned to 25fps, the fast oscillatory movements during the course provoked loss of information to a high degree. The purpose of capturing such noisy and shaky sequences is to assess the proposed algorithm against complicated and challenging situations.

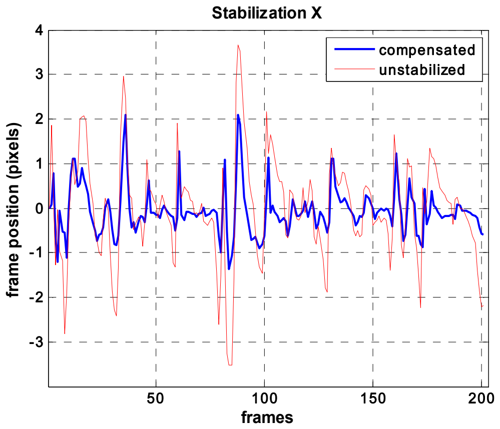


Figure 7: The red line presents each frame position before stabilization the blue line the stabilized one.

The global motion estimation did not have much computational burden, as the amount of image data has been reduced by the log-polar topology rearrangement, further restricted to four image regions. On the other hand, the differential flow technique is resource demanding. Increasing the number of iterations leads to a quite big computational load, especially to the image sequences with higher resolution. The finest results were made with a decrease of the frame resolution from the 640×480 initial Cartesian images to the 640×348 log-polar ones. Figure 7 depicts the compensation of the sequence in regard with the non stabilized frame positions.

In order to measure the performance of the stabilization made in the Cartesian and into the log-polar domain, the Mean Square Error (MSE), the Least Square Error (LSE) and the Least Mean Square Error (LSME) were calculated. From the results, it is clearly shown the superior performance of the presented technique in this paper. The estimation of the global motion vector into the log-polar plane, apart from lesser processing times, it provides also better performance.

Table 1: Error Calculation Table: The image stabilization was performed with both cartesian and log-polar images and the error calculation matrics were computed for both cases.

	Log-polar	Cartesian
MSE	0.07946845	0.08332407
LSE	0.00000226	0.00063480
LSME	0.05219010	0.0705261

5 CONCLUSIONS

A new digital image stabilization system was proposed, which employs a motion estimation optical flow model in the log-polar plane and a fuzzy system model based on Kalman filtering method. The system was fast enough although digital image stabilization is a high time consuming procedure. The global motion vector that was provided by the membership functions interaction resulted in a quite smooth output after the completion of the compensation unit. Additionally, the filtering has provided low noise levels producing a video which was free from high frequency motion effects, maintaining optimal visual quality. Concluding, the proposed system apart from having robustness and resource demands provides also optimal results fast and accurately.

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