Study on the Particle-filter-based Motion Filtering Algorithm for Digital Image Stabilization Systems

Liquan Dong*, Desen Yin, Yuejin Zhao, Mei Hui and Xiaoxiao Zhou

School of Optoelectronics, Beijing Institute of Technology
Beijing, 100081, China.

ABSTRACT

Towards to the existent problems in current motion filtering algorithms such as the low-pass filter, the Kalman filter and the extended Kalman filter. We proposed a novel motion filtering algorithm base on particle filter to separate random jitter from the global motion vectors. In this method, the variation of global motion parameters are regarded as the state-variable of system, the uniform motion model of camera is used, and the motion filtering is carried out to dynamic image sequences according to the features of digital image stabilization systems. Experimental results prove that this particle-filter-based motion filtering algorithm can achieve real-time filtering effect, and the filtering effect can be affected by the number of the particles only and almost irrespectively with other factors. This method can be used agilely and is very suitable for digital image stabilization systems application. We realized the programs based on the TI TMS320C6416DSP processing chip and got very perfect experiment results.

Keywords: Digital Image Stabilization; Motion Filtering; Particle Filtering; Motion Estimation

1. INTRODUCTION

Image stabilization is the process of generating a compensated video sequence where image motion by the camera's undesirable shake or jiggle is removed. Image stabilization techniques have been studied for decades to improve visual qualities of image sequences captured by compact and light weight digital video cameras. When such cameras are hand held or mounted on unstable platforms, the captured video generally looks shaky because of undesired camera motions. Unwanted video vibrations would lead to degraded view experience and also greatly affect the performances of applications like video coding, video surveillance, etc[1]. Many image stabilization schemes have been proposed. Among these schemes, digital image stabilization (DIS) is the most popular and in several aspects outperforms traditional electronic image stabilizer (EIS) and optical image stabilizer (OIS), both of which are hardware dependent. DIS can be implemented on hardware that is smaller than mechanical devices used for EIS and OIS, and can operate either online or offline based on different applications. DIS can also produce more precise stabilization results and operate either individually or be combined with EIS or OIS to improve the stabilization performance of EIS or OIS.

The recent image stabilizing systems are realized using digital image processing techniques instead of mechanical motion detection techniques using gyro sensors or fluid prism. Digital image stabilization (DIS) is a new generation of image stabilization technology. It obtains the information of relative motion between frames of dynamic image sequences through the method of digital image processing. Motion compensation is completed according to the information and the steady video is displayed finally. Digital image stabilization can produce stable video output, and create favorable conditions for follow-up image processing, such as image mosaic, image enhancement, information fusion, object tracking, target recognition, and so on. Meanwhile, the DIS system has many advantages over other traditional image stabilization technology, including smaller size, easy to handle and design. So DIS has a broad application prospects in military and civil fields, and has very important application value in the national defense.

* E-mail: kylind@bit.edu.cn, Telephone: +86 10 6891 2559

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The DIS system usually consists of three units, such as the motion estimation unit, the motion filtering unit and the motion correction unit, as shown in Fig. 1. In general, the motion estimation unit generates several local motion vectors from subimages in the different position of the frame using a block matching algorithm (BMA). The motion correction system determines the global motion of a frame by appropriately processing these local motion vectors, and decides whether the motion of a frame is caused by undesirable fluctuation of the camera or intentional panning. The stabilized image is generated by reading out the proper block of fluctuated image in the frame memory.

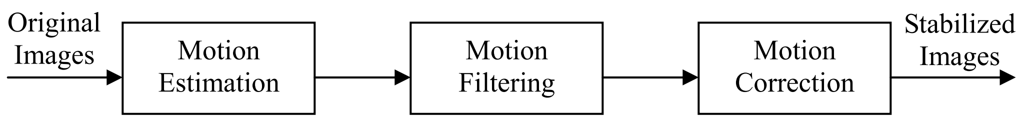


Fig. 1 Block diagram of DIS system.

2. THE PARTICLE FILTERING ALGORITHM

Particle filtering is an emerging powerful methodology for sequential signal processing, especially for nonlinear and non-Gaussian problems[2,3]. The applications include wireless communications, navigation systems, sonar, and robotics, where sequential (adaptive) signal processing is needed[4-6]. A common problem in all of these applications is the estimation and/or detection of dynamic signal parameters or states in real time. Executing different types of particle filtering algorithms on state-of-the-art digital signal processors (DSPs) suffers significantly due to lack of concurrency exploitation. Particle filters (PFs), which require a significant amount of computations, present an important challenge for hardware implementation. There are many applications where PFs can make considerable improvements in performance but often they have not been used because they cannot meet the stringent requirements of real-time processing. Hence, it is highly desirable to develop a programmable particle filtering hardware that can replace the use of DSP. In this paper, we used this particle filtering techniques to the image stabilization systems, and with the Similarity model showing as formula (1), the process of the particle filter based motion filtering algorithm are as following.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = k \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} dx \\ dy \end{bmatrix} \tag{1}$$

where θ described the image rotation leading by the camera system movement, which is always be considered as a random changed noise. And k indicated the parameter of image stretching.

2.1 System state initialization

When we begin to the motion filtering, we must confirm the variable of the system state and initialize the processing system state. We choose the variation value of the motion parameters between the images as the state variable. With the Similarity model showing as formula (1), there have small changes between the frames with θ and *k*. In order to reduce the variable dimensions and to reduce the computation, we choose $(\Delta dx, \Delta dy)$ as the variable of the system state. The initialization form are as follows:

$$T^{init} = (\Delta dx^{init}, \Delta dy^{init}) \tag{2}$$

We take the particle number as *N*, and the initialization value as 1 for the weight ω_i. Every particle directed a possible motion state or a possible position of the image. And each particle has two parameters.

$$T^i = (\Delta dx^i, \Delta dy^i) \quad , \quad i = 1, 2, \cdots, N$$

The initial value of the particle parameters are taken to be

$$\Delta dx^i = \Delta dx^{init} + b_1 \xi \quad , \quad \Delta dy^i = \Delta dy^{init} + b_2 \xi \tag{3}$$

where ξ is a random number within [-1, 1], b_1 and b_2 are constants.

2.2 System state transition

In the thereafter time of $k_t(t > 0)$, we use the system state transition equation to prognosticate the state for each particle. Suppose the system state transition equation as $x_t = Ax_{t-1} + Bw_{t-1}$. And simultaneity, where dx and dy are independent of each other. In order to reduce the calculation, we deal with them separately.

$$\Delta dx_t = A_1 \Delta dx_{t-1}^i + B_1 w_{t-1} \quad , \quad \Delta dy_t = A_2 \Delta dy_{t-1}^i + B_2 w_{t-1} \tag{4}$$

where A_1, A_2, B_1 and B_2 are constants. w_{t-1} is a random number within [-1, 1].

In the digital image stabilization processing, we take $A_1 = 1$, $A_2 = 1$ and call B_1 and B_2 as the particle transmission radius. So the meaning of the system state transition can be considered as superimposed a perturbation for Δdx and Δdy respectively.

2.3 System state observation and posteriori probability calculation

After dissemination of the various particles we can observe their state of the system. That is to say, we can observe the similarity between the image possible state and the image real state which was represented by each particle. The particle which closes to the real state is given greater weight, otherwise given the smaller weight.

We use the absolute difference function as a tool to measure the similarity. For each particle we can calculated a similar value as following

$$M^i = \left\| x_k^i - z_k \right\| \quad , \quad i = 1, 2, \cdots, Ns \tag{5}$$

where x_k^j is the Δdx or Δdy for the i^{th} particle at the time of t_k, z_k is the observation value of the system state variable at the time of t_k.

Then define the observe probability density function as

$$p(z_k \mid x_k^i) = \exp\left\{ -\frac{1}{2\sigma^2} M^i \right\}$$

where σ is a constant.

Using the observe probability density function, we can do Gaussian modulation for the relevant values. So the weight for each particle can be recursive calculated as following:

$$w_k^i = w_{k-1}^i p(z_k \mid x_k^i) \tag{6}$$

For the posteriori probability at the time of k_t , is the expected motion parameters variation value $\left(\Delta dx_t^{opt}, \Delta dy_t^{opt}\right)$ for image motion trajectories, can be expressed by the weight summation of each particle.

$$\Delta dx_t^{opt} = \sum_{i=1}^{NS} w_t^i \Delta dx_t^i \quad , \quad \Delta dy_t^{opt} = \sum_{i=1}^{NS} w_t^i \Delta dy_t^i \tag{7}$$

At this point, we finished one filtering process. The filtering process for the next time will still re-start with the system state transition step.

2.4 Re-sampling

After several recursive for above process, except to fewness particle, the weight for the rest particle can be negligible. So a large number of calculations are wasted in many update of the particle which has almost nothing contribution, or only leaving an effective particle with large weight. While the weights of the other particles are close to zero. To avoid this problem, we can use the Re-sampling strategy[7]. The core idea of this re-sampling strategy is to increase the particle with large weight and kick out the particle with small weights. The effective particle number in our experiment is N_{eff} , which is defined as

$$N_{eff} = \frac{1}{\sum_{i=1}^{N} \left[w_k\right]^2}$$

We can pre-defined a threshold value as N_{th} , if $N_{eff} < N_{th}$, we use the re-sampling process, otherwise, without the re-sampling process.

3. EXPERIMENT AND RESULTS


(a) The 10th frame


(b) The 20th frame


(c) The 30th frame


(d) The 40th frame

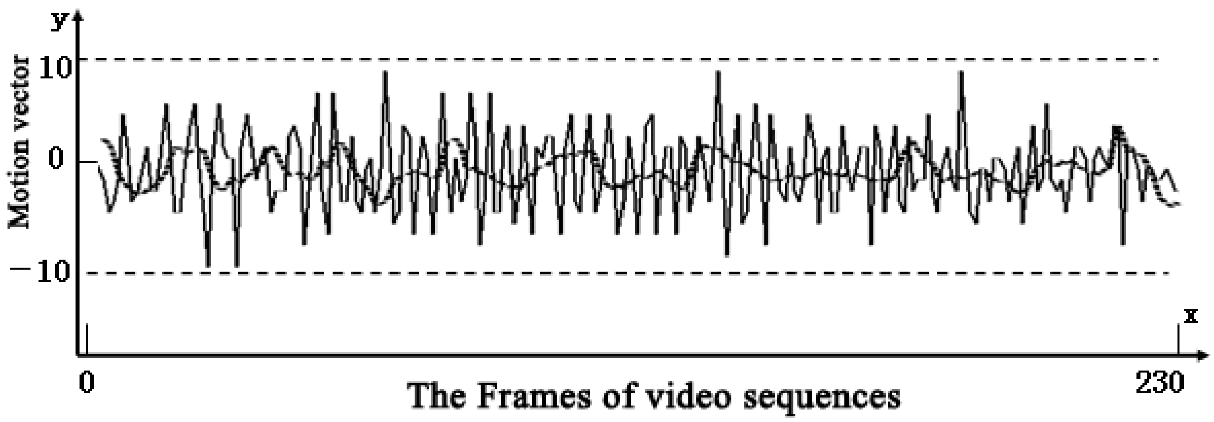

(e) The 50th frame


(f) The 60th frame

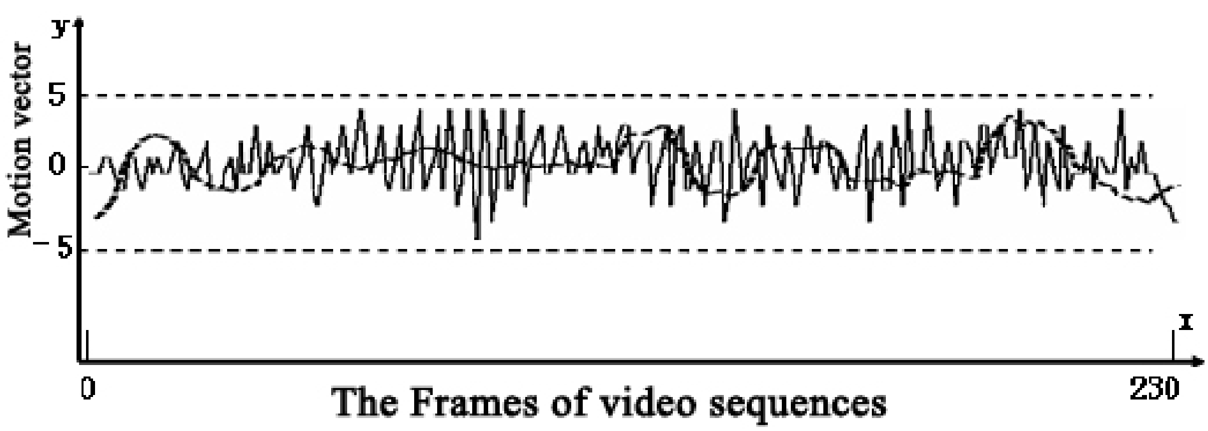
Fig. 2 The original images from the video sequences

In our experiment, we fixed the camera system on the vehicle with rigid fastening. The vehicle was driven on the uneven road surface, while we saved image frames with the camera system. And we use these saved image frames as our processing objects. There are about 231 image frames in our selected video sequences. The image resolution is 320 × 240 pixels. We use our particle filter based motion filtering algorithm to process these image frames with VC++ programs on the personal computer. A few image frames selected from the video sequences are showing in Fig. 2.

Firstly, we doing the motion estimation based on the block-matching methods. Then removed the "outliers" based on the least-squares methods and calculate the global motion parameters. And then, we use the particle filter based motion filtering algorithm on the image sequences filtering. In our experiments, we choose the particle transmission radius with 7 pixels, and the coefficient of the particle state transition as 1, with the particle number as 100, 200 and 500 respectively. The filtering results are showing in Fig.3, Fig. 4 and Fig. 5 respectively.

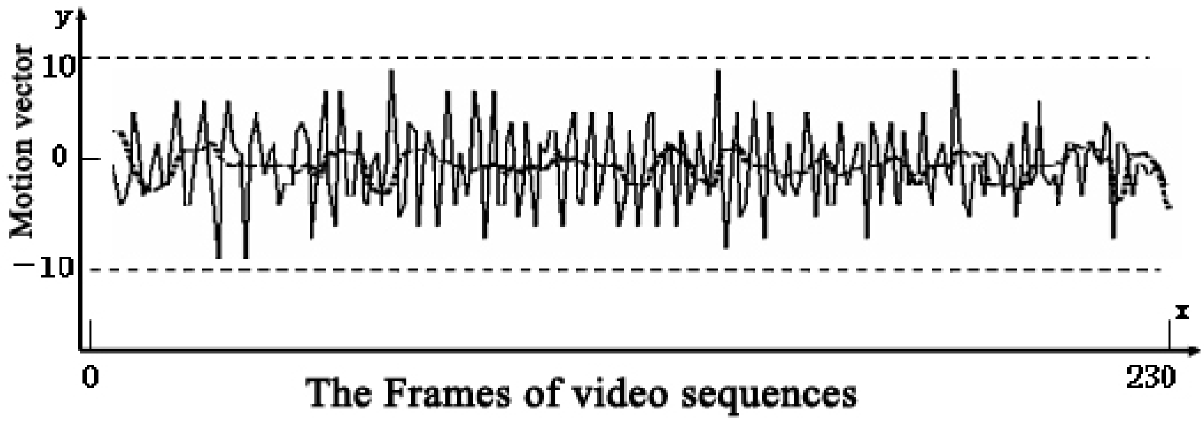


(a) The variation curve of the motion vector in x direction

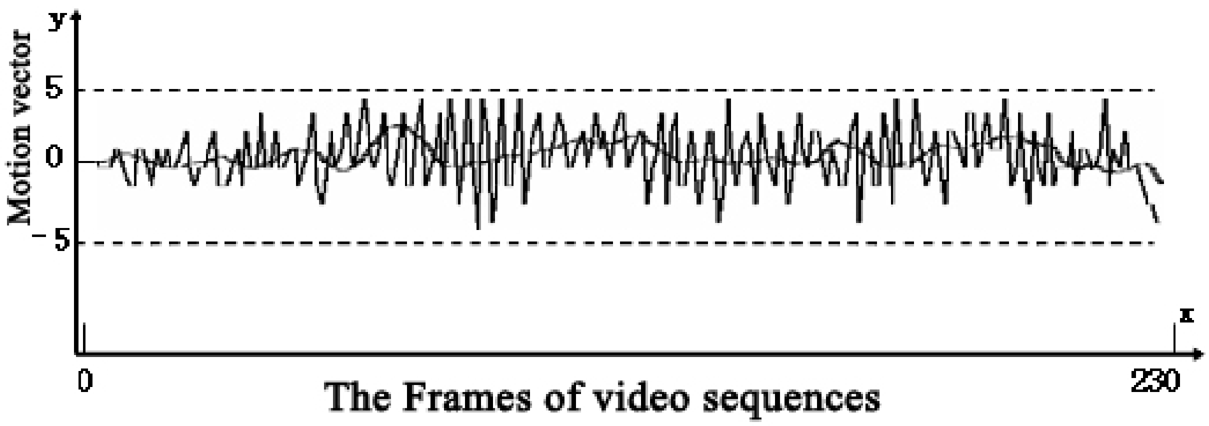


(b) The variation curve of the motion vector in y direction

Fig. 3 The filtering result with the particle number of 100

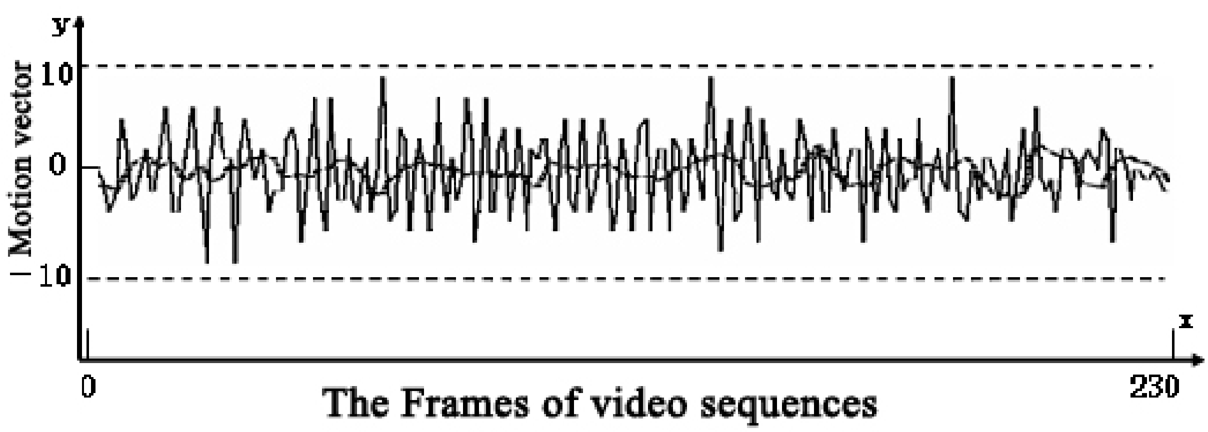


(a) The variation curve of the motion vector in x direction

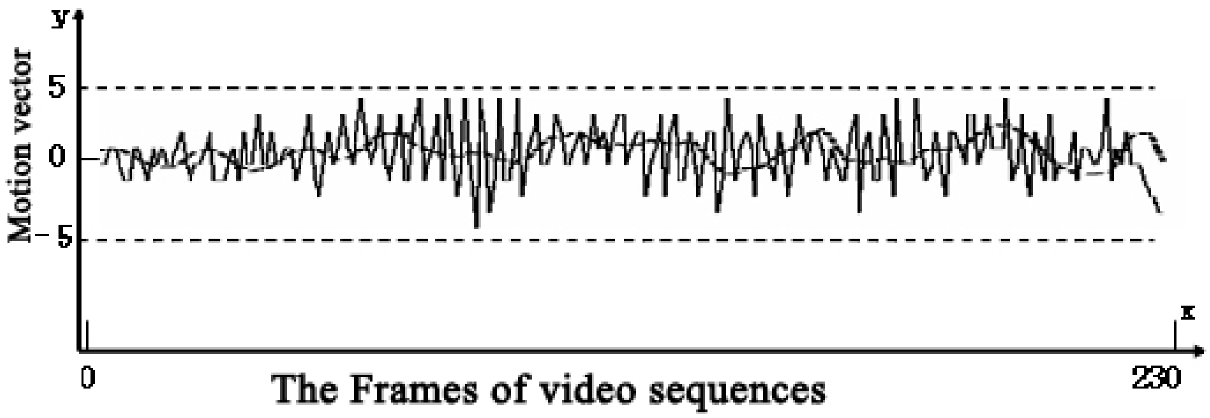


(b) The variation curve of the motion vector in y direction

Fig. 4 The filtering result with the particle number of 200



(a) The variation curve of the motion vector in x direction



(b) The variation curve of the motion vector in y direction

Fig. 5 The filtering result with the particle number of 500

From the experiment result we can find:

(1). The particle filter has a good filtering effect motion filtering.

(2). The filtering effective of the particle filter are related with the number of the particle. The more with the particle number, the filtering effective will be better.

(3). The particle filter algorithm does not require a certain time delay, the initial value of the other parameters will not take obviously effect for the filtering results.

So this filtering technique based on the particle filtering algorithm is effective and feasible exercise, which is very suitable for applications in the digital image stabilization system.

4. CONCLUSIONS

Digital image stabilization is a very useful technique for improving the visual quality of the video sequences captured by compact and light weight digital video cameras. In this paper, a particle filter based motion filtering algorithm was described. Which algorithm is an emerging powerful methodology for sequential signal processing, especially for nonlinear and non-Gaussian problems. The experimental results show that the proposed particle filter based motion filtering algorithm can generate more precise motion parameters and has higher processing capabilities for different motions compared with mean filter or Kalman filter based algorithm.

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