Measurement 44 (2011) 96–101

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

A multiscale optimal filter method for micro-motion measurement with high accuracy

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ARTICLE INFO

Article history:
Received 7 April 2009
Received in revised form 4 September 2010
Accepted 14 September 2010
Available online 21 September 2010

Keywords:
Motion estimation
Filter design
Gradient
Multiscale

ABSTRACT

Micro-motion measurement plays an important role in technologies such as micro/nanomanufacturing and biomedicine. In this paper, micro-motion measurement is viewed as a signal processing problem, and the measured image gradients are estimated using the filter methods. A class of optimal filters for image gradient calculation is designed according to Parks–McClellan algorithm. In combination with multiscale approach, a multiscale optimal filter method for micro-motion measurement is proposed. In such a method, the larger motions are converted into multiple small motions to measure, thus the measurement accuracy can be further improved. The maximal bias magnitude of this proposed method reached 0.0064 pixels for the motions near 2 pixels. Experimental simulations show this proposed multiscale optimal filter method can measure the micro-motion with high accuracy.

1. Introduction

Micro-motion measurement with high accuracy is critically important for exploring the high technologies such as micro/nanomanufacturing and biomedicine [1,2]. In existing noncontact optical methods for micro-motion measurement, computer microvision approach offers a number of advantages over other optical approach. For example, the target whose micro-motion is being measured is unambiguous in computer microvision, because the micro-motions are determined directly from video images. In combination with motion estimation algorithms, computer microvision method can measure the micro-motion with high accuracy [3].

In the last two decades, researchers have proposed a number of algorithms for motion estimation. These approaches may be divided into two broad categories, namely correspondence based and gradient based. Gradient-based algorithms deliver image motion information using spatial and temporal variations of image intensity at every point [4]. Furthermore, gradient-based algorithms can be used to register arbitrary images and no prior knowledge of the target is needed [5–7]. One popular class of methods for estimating motion is the gradient-based methods for the above mentioned advantages, which require measurements of image gradients [6]. Previously, majority of groups calculated the image gradients using first-order difference methods [9,10]. However, this approach provides inferior accuracy for motion estimation. Subsequently, the image gradients are measured in a way of filters [11,12]. Farid and Simoncelli designed a general differentiator filter using error function [10], but the authors have not addressed the design of filters specifically for application to motion estimation. In Ref. [11], Timoner and Freeman referred to the gradient filters as convolution of the discrete images with linear filters, thus they developed a class of algorithms for motion estimation based on multidimensional digital filters. This filter technique can measure MEMS motion with nanometer accuracy. However, this approach provides relatively poor estimation performance for motions larger than 1 pixel in magnitude.

In this paper, micro-motion measurement is viewed as a signal processing problem. Image gradient is referred to

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doi:10.1016/j.measurement.2010.09.030

as convolution measured images and optimal filters, and the optimal filters are designed. A new integrated approach that incorporates multiscale technique into the optimal filter method is proposed.

2. Gradient-based motion estimation

Many motion estimation algorithms are proposed based on gradient constraint. Though there are different ways to derive the gradient constraint, the gradient-based methods emerge all from the assumption that the intensity value of a physical point in a scene does not change along the image sequence, and this is the so called brightness change constraint equation [9]. This constant brightness assumption on two consecutive images can be expressed as,

$$I_x(x,y,t)d_x + I_y(x,y,t)d_y + I_t(x,y,t) = 0 \quad (1)$$

where $I_x(x,y,t)$, $I_y(x,y,t)$ and $I_t(x,y,t)$ represent gradients of the image intensity $I(x,y,t)$ in the x, y and t directions and $\mathbf{d} = (d_x, d_y)^T$ represents the local displacement in the x and y-directions at time t, respectively. After computing the value of the gradients at many different locations, Eq. (1) can be expressed as an overconstrained set of equations with the two unknown d_x and d_y. For simplicity, I_x, I_y and I_t is used to represent $I_x(x,y,t)$, $I_y(x,y,t)$ and $I_t(x,y,t)$, and the solution of this set of equations has the form using the method of least squares,

$$\begin{bmatrix} d_x \\ d_y \end{bmatrix} = -\begin{bmatrix} \sum_{i,j} I_x I_x & \sum_{i,j} I_x I_y \\ \sum_{i,j} I_x I_y & \sum_{i,j} I_y I_y \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i,j} I_x I_t \\ \sum_{i,j} I_y I_t \end{bmatrix} \quad (2)$$

where the values of d_x and d_y are over i and j, and all values are at time t. Here, $0 \leqslant i < M$, $0 \leqslant j < N$, and $M \times N$ represents the number of pixels in measured images.

Note that the values of d_x and d_y can be obtained from the Eq. (2) after determining the image gradients. The image gradients are estimated using the first-order difference, originally proposed by Horn and Schunck [9], but this approach offers inferior estimation accuracy. In this paper, micro-motion measurement is referred to as a signal processing problem, and the gradients are calculated using filter methods. The gradients of the image intensity can be estimated by convolution of the images with gradient filters,

$$I_x(x,y,t) = [(I_1(x,y,t) * g) * h^T + (I_2(x,y,t) * g) * h^T]/2$$

$$I_y(x,y,t) = [(I_1(x,y,t) * h) * g^T + (I_2(x,y,t) * h) * g^T]/2$$

$$I_t(x,y,t) = I_2(x,y,t) * h - I_1(x,y,t) * h \quad (3)$$

where g is a derivative filter, h is an interpolation filter, T is transpose operator, and * represents convolution. From Eq. (3), one can find that the process of calculating the gradients of image intensity is equivalent to finding the available filters. The values of d_x and d_y can be further found after choosing the filters. In order to measure micro-motion, the optimal filter for computing the image gradients is designed in the following section.

3. Optimal filter design for motion estimation

As shown in Eq. (3), the gradient estimate can be considered as a convolution of the measured image with a set of one-dimensional filters in each direction. The general gradient calculation in the x-direction, for example, consists of a convolution of two successive images with a derivative filter in the x-direction and an interpolation filter in the y-direction, respectively.

The Parks–McClellan algorithm [12] is a popular class of approaches to designing the filters. In this paper, the Parks–McClellan algorithm is used to create the filters for image gradients calculation. This method requires a desired filter response $H_d(\omega)$, the desired length of the finite impulse response filter, and a weighting function $W(\omega)$ which determines the relative importance of errors as a function of frequency, where ω represents the spatial frequency. In the Parks–McClellan algorithm, the filter $A(\omega)$ can be determined by minimizing the maximum of the absolute value of the weighted error $E(\omega)$, and the absolute value of $E(\omega)$ is given by,

$$|E(\omega)| = |W(\omega)[H_d(\omega) - A(\omega)]| \quad (4)$$

To use the algorithm, the appropriate error weighting function need to be determined first. For the majority of the microstructure images from the computer microvision, there is little signal energy above spatial frequency 2, where π is the Nyquist frequency. Therefore, the weighting function can be expressed as [13],

$$W(\omega) = \begin{cases} \omega^{-1} & 0 \leqslant \omega \leqslant 2 \\ 0 & 2 < \omega \end{cases} \quad (5)$$

All the derivative and interpolation filters were calculated using Matlab "*firpm*" function, and then the gradients of the image intensity can be computed using these designed filters according to Eq. (3).

The magnitude of the frequency response of an ideal derivative filter is ω because the derivative of $e^{-j\omega x}$ is $-j\omega e^{-j\omega x}$. Several example derivative filters are shown in Fig. 1a. An ideal interpolator has a magnitude response of 1. Fig. 1b exhibits several example filters. Fig. 1 shows the derivative filters with odd length better approximate the ideal derivative filter than the even-length derivative filters of comparable length, and the interpolation filters of odd length is also a best approximate of the ideal interpolation filter.

In the process of acquiring measured images, the nonzero acquisition time smoothes temporal changes in brightness, and blurs moving microstructure, thus leads to directly motion estimation errors [14]. This effect can be modeled as a low-pass filter temporal filter, and the effects of blurring can be counteracted by designing temporal derivative and interpolation filters. The inverse filter with $H(e^{j\omega}) = [\sin(\omega/2)]/(\omega/2)$ which is shown in Fig. 2 can compensate for the motion estimation errors caused by the effects of blurring [11]. The curve in Fig. 2 illustrates the magnitude change of the temporal compensation filter with the spatial frequency.

Combining the temporal compensation filter into the designed filters based on the Parks–McClellan algorithm,