Investigation of the Limitations of the Motion Estimation Algorithms for Measuring MEMS in-plane vibrations

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ABSTRACT

Stroboscopic Illumination is a technique used for in-plane vibration measurements for MEMS devices. An easy to implement and cost efficient method for motion estimation is using sub-pixel image processing algorithms with stroboscopic illumination. This paper investigates the limitations and accuracy range of different image processing algorithms for the measurement of in-plane vibration of MEMS devices. The performance of such algorithms is investigated for various experimental variables and the optimum conditions are studied for obtaining accurate results.

Keywords: stroboscopic illumination, MEMS, in-plane vibrations, image processing algorithms

1 INTRODUCTION

Rapidly growing developments in MEMS devices created a necessity for reliable testing methods for dynamic characterization. There are several methods for vibration measurements but most of them uses out of plane displacements. In order to calculate vibration modes, out of plane measurements are not enough for most cases and in plane measurements are required. Several methods have been suggested by various authors, such as electronic speckle pattern interferometry [1], holographic techniques [3,4] and two laser beam heterodyne techniques. Moiré techniques [5] and laser Doppler interferometry [6] can also be used for in plane measurements but they need specific structures or arrangements to produce correct results.

An easy to implement method was purposed by Freeman and his colleagues at MIT Computer Vision Facility [7]. This author showed that an ordinary scientific camera can be used to measure MEMS motion in nanometer scale by using stroboscopic illumination and subpixel image processing algorithms. This method has been used by several authors [8,9,10] and a commercial vibrometer was also produced [11]. There is also literature on some image registration algorithms tested for this method [12,13] and an updated version for three dimensional vibration measurements [14]. In the Stroboscopic Illumination technique, a device vibrating periodically at a higher frequency than the camera frame rate is illuminated with very short light pulses. These light pulses coincide to the same point of displacement in vibration cycle of the specimen and several images are integrated at one camera frame. Vibrating device is seen as it is frozen at a certain point of its cycle and different points of the cycle can be viewed by introducing delay to light pulses. The amount of displacement at four different points of the sinusoidal motion of the specimen at sub-pixel level can be calculated using motion estimation algorithms.

In this study, we used two different commonly used motion estimation algorithms; Lucas Kanade and Phase Correlation to estimate the known displacement of a MEMS device. Although the previous studies used similar algorithms , they were mainly concentrated on the accuracy of the motion estimation under optimal and some sub-optimal conditions. However, we extended these studies such that we investigated a quite number of experimental variables such as 1-50 pixel displacement range, and various illumination duty cycles changing from 1%-100% brightness. We quantified the performance degradations and also determined the conditions where these algorithms failed. We also investigated the effect of common noise filtering alternatives on the performance of the motion estimation algorithms for various experimental conditions. This study presents our preliminary results in determining the most suitable conditions and algorithm to estimate the known in-plane displacement of a MEMS device. Once the most suitable conditions are obtained and the most accurate algorithm is determined, the same procedure can be applied to estimate the displacement of a vibrating MEMS device using the Stroboscopic Illumination technique.

2 EXPERIMENTAL SETUP

The experimental setup that was developed in our laboratory for out-of-plane measurements were extended to include the in-plane vibration analysis with some extra equipment [15]. This equipment includes a Stroboscopic Illumination Device (SID) that was constructed using a high brightness light-emitting diode (LED) and a high frequency modulatable driver. For syncronization, the driving signal of the specimen and the SID are generated by the same signal generator. Phases of the driving signal of the SID are adjusted by using the delay-pulse generator. Image processing and acquisition is done using MATLAB toolboxes and C++ with OpenCv library.

3 THE FACTORS INFLUENCING THE PERFORMANCE OF THE METHOD

In this study, we only present our results for images of a MEMS device with known displacement along the x direction. Once the accuracy of these algorithms is determined for various experimental and specimen conditions, they can be easily adapted to Stroboscopic Illumination technique to estimate the displacements of a vibrating MEMS device. In order to obtain accurate results, limitations of the Stroboscopic Illumination technique and the motion estimation algorithms must be studied carefully. Such limitations are due to the nature of the illumination technique, image characteristics of specimens, experimental conditions, equipments used in the setup, and the nature of the motion estimation algorithms.

In the Stroboscopic Illumination technique, in order to maintain the sharpness of the images, illumination time needs to be as small as possible which reduces the percent of the vibration cycle subjected to illumination [7]. This situation reduces the brightness of the images also reducing signal to noise level. For this purpose, performance of the motion estimation algorithms must be studied under low brightness levels.

The motion estimation algorithms used in this study are generally used for calculating motion between successive frames of general purpose video. A general video is usually assumed to have little motion between successive frames compared to the motion of a vibrating MEMS device. Also a general video is usually considered to have continuous variations of gradients [2]. In a typical picture of a MEMS device, continuous variation of gradients are less expected due to the nature of the MEMS structures but sharp gradients at the borders of the device can be easily found [2]. Magnification of the specimens contributes to this condition. In order to deal with this situation, tracked points should be selected carefully in order to find the points with largest variation. In this study, we chose a MEMS specimen (see Figure 1) satisfying all these conditions and we developed a metric to quantify the contrast level of the specimen which will be outlined in the following section. This number and the signal to noise ratio can be used as indicators for the performance of the motion estimation algorithms to select the most suitable specimen for motion estimation.

The noise generated by CCD and optical components reduces the signal to noise ratio and causes motion estimation algorithms to give erroneous results [7]. In order to obtain an optimum performance, understanding and removal of the noise is beneficial. Signal to Noise (SNR) levels and variance of the noise must be calculated to understand the nature of the noise that is present in the system.

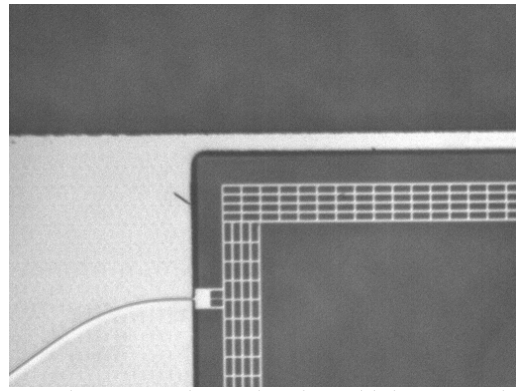

Figure 1: The test specimen showing a high contrast level.

Experimental conditions may also affect the performance of the method. Unwanted background illumination at the experimental setup causes noise at the images and substrate vibrations results in blurring. In order to prevent this, experiments are done with light isolation and a vibration table is used for substrate vibrations.

4 MOTION ESTIMATION ALGORITHMS

There are several algorithms available for motion estimation. These algorithms are widely used in video compensation. Previous studies showed that Lucas Kanade and phase correlation algorithms can be successfully used for determining one and two dimensional motion [7,13]. Studies done with Lucas Kanade and Horn Schunk showed that Lucas Kanade produces more reliable results [13]. Other studies with Phase Correlation showed that it is a much faster and easier technique than gradient based algorithms [16]. Based on the results of these previous studies, we chose Lucas Kanade and Phase Correlation for our experiments.

Phase Correlation is a well known method that uses the frequency domain in order to find the shift in the signal domain. Two successive frames are considered as shifted signals and cross correlation between these signals are supposed to be maximum at the point where wave forms match each other. This point corresponds the shift of two signals. [murat tekalp]Using FFT (Fast Fourier Transform) and frequency domain for cross correlation is a fast way to calculate this shift. Processing is done using the procedure described in [16].

Lucas Kanade algorithm uses spatial gradients to find the best match of selected points at reference image to the displaced image. Algorithm computes the intensity gradient of the reference frame at selected points and searches for these points in the displaced image. Result is an optical flow field of motion vectors at selected points. Algorithm we used is the pyramidal version of Lucas Kanade with 5

pyramids in order to determine the motions at 50 pixel range [2].

Both methods have advantages and disadvantages. Phase Correlation is a much faster algorithm which is easy to implement. The performance of the algorithm is affected with the shape of the wave form so difference of the illumination level of two images does not change the results. It is also less affected by Gaussian noise but it strictly depends on the signal shape of the processed area and gives a single result. Since it assumes circular shift of the signal, it is expected to produce slight errors if the image does not satisfy this condition. On the other hand Lucas Kanade is a much more computationally expensive algorithm and much more affected by random noise since it depends on calculation of the gradients.

5 NOISE FILTERING

There are two types of fundamental noise that need to be considered for the experimental setup. These are fixed pattern and shot noise. Fixed pattern noise is generated due to the imperfection of the response of the CCD array pixels and dirt in the optical components. Shot noise is due to the quantum nature of light [7]. Also illumination level changes the noise and signal strengths on the image and affects the SNR. The variation of SNR is plotted as a function of brightness level in Figure 2.a. The variance of the noise is also plotted as a function of brightness level in Figure 2.b. For noise filtering, Gaussian, Wiener, Median and Average filters have been tested using standard MATLAB routines. A 3x3 window is chosen in order to preserve intensity gradients. Also an averaging algorithm is used in order to take average of all images. Because of the random nature of the shot noise, averaging produces most satisfactory results but presence of fixed pattern noise prevents additional noise removal with this method. Wiener and Median filtering produces similar results but Median filtering is known to preserve gradients better. Gaussian filter produces lowest SNR apart from no filtering case. Average filter produces good results when SNR and noise variance is taken into account but it also degenerates the gradients most. The low SNR values at 1% brightness level indicates important distortions on the images. When contour plots at this brightness level are examined, it is seen that variations of the intensity values prevents signal to be perceived correctly and filtering algorithms are not very effective.

6 MOTION ESTIMATION WITH KNOWN DISPLACEMENT

In order to quantify the contrast level of the specimens, we used two numbers for gradients. We defined a Gradient Contrast Number (GCN) which is the ratio of mean of the lower pixel values to the mean of higher pixel values in a region at the start and end of a gradient at full illumination (100% brightness level). With lower brightness level, contrast of the image changes, another number called Modified Gradient Contrast Number (MGCN) is also defined. For the specimen that is used in this study, the image intensity values of the device and background are nearly uniform, so the calculation is carried out using the whole image and only one MGCN value is calculated for each brightness level. If the device has gradients with different contrasts, more than one MGCN should be calculated. Table 1 tabulates MGCN values for different illumination levels for the specimen used in this study.

$$GCN = \frac{\sum I_{high} / n_{high}}{\sum I_{low} / n_{low}} \quad \text{for 100\% brightness}$$

$$MGCN = \frac{\sum I_{high} / n_{high}}{\sum I_{low} / n_{low}} \quad \text{for lower brightness}$$

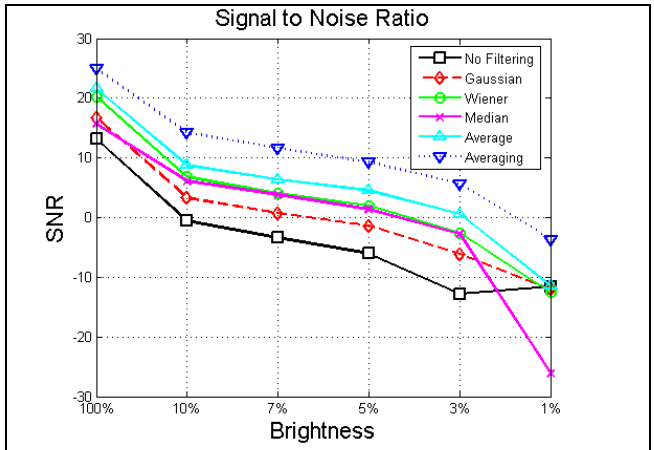

Figure 2.a Variation of Signal to Noise ratio as a function of brightness.

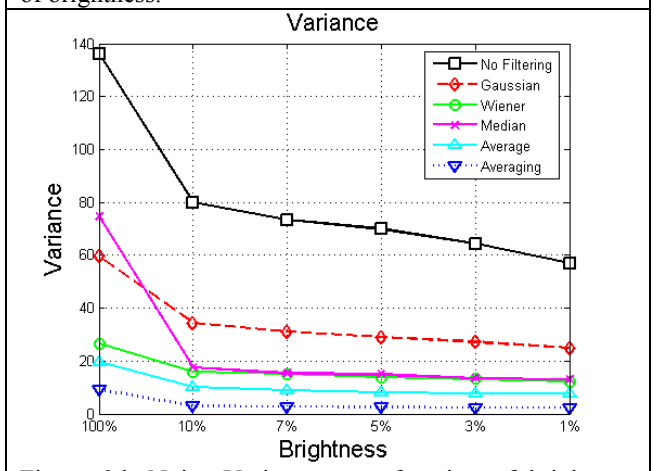

Figure 2.b Noise Variance as a function of brightness level.

Table 1: MGCN values for different brightness levels.

Brightness	MGCN	Mean High Pixel Value	Mean Low Pixel Value
100%	0.429	223.1	95.8
10%	0.548	42.3	23.2
7%	0.597	32.5	19.4
5%	0.6481	25.3	16.4
3%	0.691	18.1	12.5
1%	0.877	12.2	10.7

Figure 3 shows the variation of the errors in estimating the known displacements of 1, 2, 6, 10, 20, 30, 40 and 50 micron in x direction using Lucas Kanade and Phase correlation algorithms (1 pixel = 1.04 micron). Figure 3 also shows the effect of noise filtering on the performance of the motion estimation algorithms under 100% brightness level. Both algorithms perform well under 100% brightness level and the errors are within 1-2 micron range for all the displacements. Filtering does not significantly change the results under full brightness level. Same procedure is also repeated for different illumination levels and images with 10%, 7%, 5%, 3% and 1% are captured. Figure 4.a shows the variation of the error obtained using the Lucas Kanade algorithm for different displacements under 3% illumination level with an MGCR of 0.691. Although results of the filtering options are very close to each other, averaging generally produces slightly better results. SNR of averaging at this brightness is 24.929. For lower brightness levels, the algorithm fails and produces large errors which increase with increasing displacement. Figure 4.b shows the error variation obtained using phase correlation algorithm under 7% brightness. At this brightness MGCR is 0.597. Phase correlation algorithm becomes unreliable and produces large errors under lower brightness.

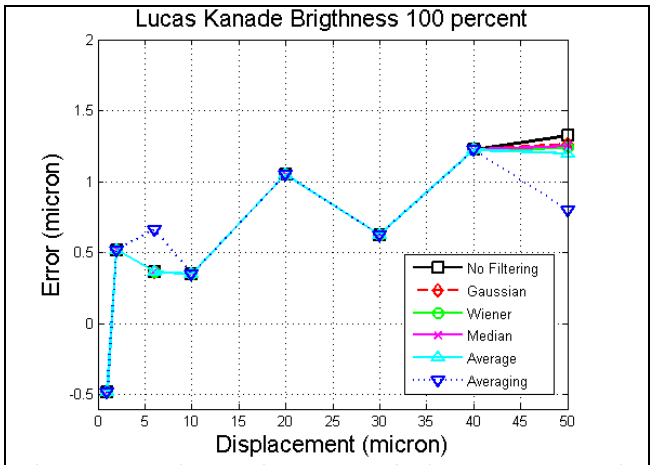

Figure 3.a The performance of the Lucas Kanade Algorithm for 1-50 micro displacement range under full brightness.

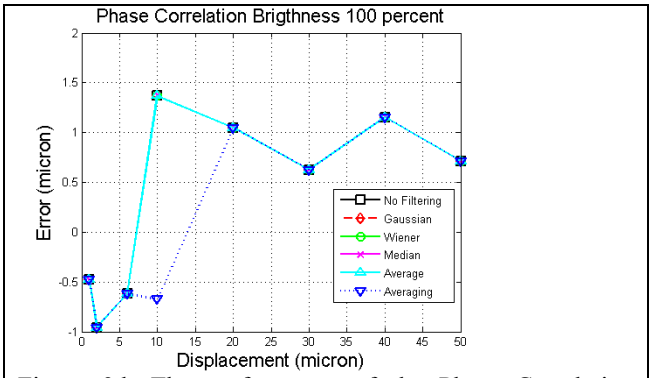

Figure 3.b The performance of the Phase Correlation algorithm for 1-50 micro displacement range under full brightness.

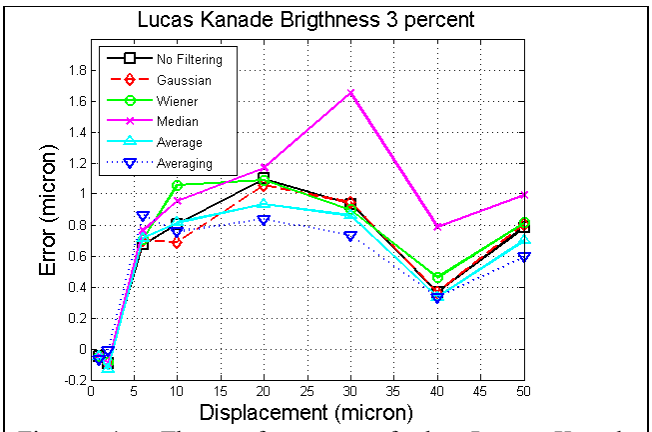

Figure 4.a The performance of the Lucas Kanade algorithm for 1-50 micron displacement range under 3% brightness.

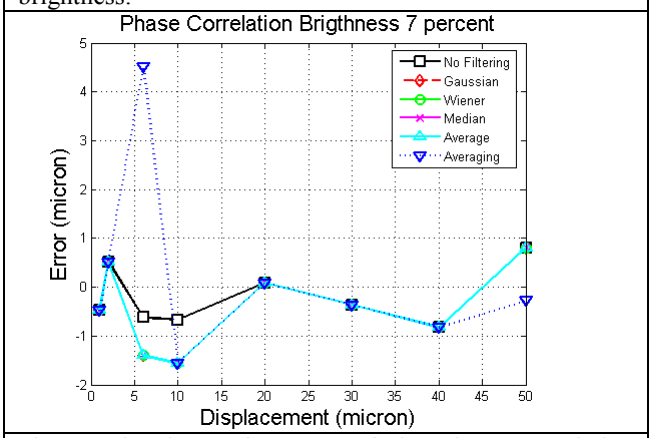

Figure 4.b The performance of the Phase Correlation algorithm for 1-50 micron displacement range under 3% brightness.

7 CONCULUSION

In this study, we investigated the limitations and accuracy range of Lucas Kanade and phase correlation algorithms for the measurement of in-plane vibration of

MEMS devices. The errors in the estimation of known displacements were calculated and the results were compared to identify the optimum conditions for accurate motion estimation. Several noise filtering options such as Gaussian, Wiener, Median, and Average filters were tested and their effects on the performance of the motion estimation algorithms were determined. It was observed that Lucas Kanade performed better than the phase correlation algorithm when the brightness level dropped. It was also observed that when the SNR level is low, phase correlation algorithm fails before Lucas Kanade.

Also the quantification of gradients was made by defining a contrast measure for the specimen. This number can be used to select the most appropriate specimen or portion of the specimen for motion estimation. The techniques developed in this study can be easily adapted to to estimate the displacement of a vibrating MEMS device using the Stroboscopic Illumination technique.

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