New image processing tools for structural dynamic monitoring

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Abstract. This paper presents an introduction to structural damage assessment using image processing on real data (non ideal conditions). Our contribution is much more a groundwork than a classical experimental validation. After measuring the bridge dynamic parameter on a small resolution video, we conjointly present advantages and limitations of our method. Finally we introduce several "computer vision" based rules and focus on the technical ability to detect damage using camera and video motion estimation.

Introduction

In mechanical engineering, modal control is widely used to assess civil engineering structures by means of vibration measurement. Indeed vibration monitoring is a low cost and non destructive tool which could even be used with natural excitation (wind, traffic...). The paradigm of Structural Health Monitoring (SHM) approach in damage detection is based on the assumption that modifications of structural properties will alter the dynamic characteristics of the structure (i.e., resonant frequencies, modal damping and mode shapes) [4]. Many researchers [5,8,9] focused their studies on the characterization of the structural mode shapes which contain spatial information and appear to be more sensitive to the presence of damage zones than natural frequencies. The goal of our work is to develop a method to replace classical contact accelerometers based instrumentation with an optical camera working with an intelligent software to continuously assess the dynamic parameters (frequency, damping and mode shape) of the structure under study. Previous works [10,11,13] obtained modal parameters in introducing real targets on the structure or in studying simple structure in ideal conditions. Our goal is not to compare our method with classical modal testing but to show the ability of both high speed camera and openCV framework to easily reconstruct displacement from a simple video (the step of verification can not be done since the video is not our work). In some applications, video camera can replace accelerometer for bending displacement estimation under 2 hypothesis: firstly the number of Frame Per Second (FPS) respect the Nyquist frequency criteria and secondly the plan of study is perpendicular to the studied 2D structure (small angular errors).We introduce an advanced motion estimation algorithm [7] to reconstruct the displacement signals under linear displacement hypothesis. They are obtained using Lucas-Kanade "optical flow" algorithm [3] under OpenCV [15].
The paper is organized in 3 chapters, the first introduces the theoretical background of system identification in structural vibration. The second part discusses of the "optical flow" algorithm and describes the originality of the technique to reconstruct continuous displacement signals from non complete motion data. We also validate our advanced method in using video (http://home.messiah.edu/~barrett/Video.html). The video (2harmonicside.mpeg[1]) is the second harmonic dynamic response of a suspension bridge excited by human loading. Finally the third section is focused on the technical ability to detect damage using camera and video motion estimation while proposing innovative approaches in dynamic structural monitoring.

[1] It won the first prize in the 1972 American Association of Physics Teachers Biannual Film Competition

System identification in structural dynamics

Basically, modal analysis is the study of the natural characteristics of structures. Understanding the natural frequency, damping and mode shape helps to design structural system for noise and vibration applications. Modal analysis is generally used to design/monitor all types of structures including automotive structures, aircraft structures, spacecraft... The main approach to obtain the modal model is the so-called Experimental Modal Analysis (EMA), which is based on the measured forces and vibration responses of the structure excited in one or more locations. More generally, the process of finding a model from the data is called system identification, originating from the domain of electrical engineering. The Fourier Transform enables to obtain the frequency response function ($H(j\omega)$ with ω in rad/s) function of the displacement signal s(t) and excitation signal e(t) as:

$$H(j\omega) = \frac{S(j\omega)}{E(j\omega)} \tag{1}$$

Moreover, as a direct result of the emerging information technology significant advances have been available to both modal test and analysis equipment, explaining the increasing interest for EMA.
Operational Modal Analysis (OMA) is defined as the determination of a modal model obtained by response testing only [12]. So no measurement of input forces are required and measurement procedure is similar to Operational Deflection Shapes (ODS) measurement. The main interest of this method is the determination of modal model under operational conditions (*in situ* testing). Moreover since it is used successfully in civil engineering applications (ambient or natural excitation for bridges and buildings) it begins to be introduced in mechanical engineering applications like rotating machinery or in-flight testing. Two main signal processing method exist: frequency domain technique like Frequency Domain Decomposition (FDD) using Singular Value Decomposition (SVD) or time domain technique like time data driven algorithms using Stochastic Subspace Identification (SSI). Table 1 tries to resume important drawbacks and interesting advantages dealing with the OMA method:

Drawbacks	Advantages
• Unscaled (non calibrated) modal model • Some *a priori* knowledge is advantageous • New technique to most engineers • Large time histories might be required: more data handling capacity is needed (higher computational cost)	• No elaborate fixture of shakers and force transducers • Short setup time • No crest factor problems as when using hammers • No potential destruction of structure • Modal model represent real operating conditions • True boundary conditions • Actual force and vibration levels • Ambient or unmeasured excitation required • No interference or interruption of daily use

Table 1: Benchmark of operational modal analysis

Image processing method for dynamic parameter extraction

A way to detect moving objects is by investigating the optical flow which is an approximation of two dimensional flow field from the image intensities. It is computed by extracting a dense velocity field from an image sequence. The optical flow field in the image is calculated on basis of the two assumptions that the intensity of any object point is constant over time and that nearby points in the image plane move in a similar way [1]. Additionally, the easiest method of finding image displacements with optical flow is the feature-based optical flow approach that finds features (for

example, image edges, corners, and other structures well localized in two dimensions) and tracks their displacements from frame to frame. The LK [7] tracker is based upon the principle of optical flow and motion fields [1,2,3,7] that allows to recover motion without assuming a model of motion. OpenCV means Intel® Open source Computer Vision Library [15]. It is a collection of C functions and a few C++ classes that implement some popular computer vision algorithms. We use the function cvCalcOpticalFlowPyrLK which implements sparse iterative version of Lucas-Kanade optical flow in pyramids [3]. It calculates coordinates of the feature points on the current video frame given their coordinates on the previous frame with sub-pixel accuracy.
For practical purposes we use this algorithm on the bridge video in order to track the motion of the target pixels (Figure 1). It offers various advantages like stable and accurate motion results in non optimal environment.

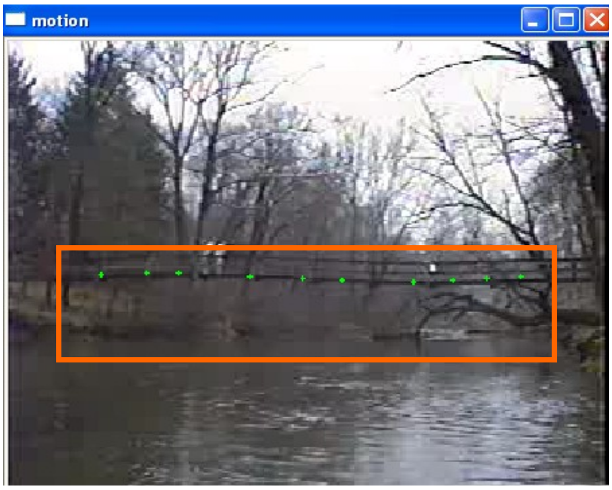

Figure 1: Example of motion estimation, using an adaptation of lkdemo algorithm. The 10 initialization points are in green full circle and the zone under study is in orange.

But this algorithm also offers some drawbacks: no motion can be detected in several zone of the image due to low contrast (73 % of the tracked points are used to reconstruct mode shapes). Moreover the main problem occurs in signal reconstruction (displacement). In fact target pixels which move around x axis create partial modal data (so displacement signals are irregular data). To compensate the missing data (Figure 2), we use the small linear displacement hypothesis to enhance the resolution of the motion. If the absolute value of x abscissa relative displacement is less than 3 the data is used, if not , the data is not used (a correct percentage of 27 % of loss).

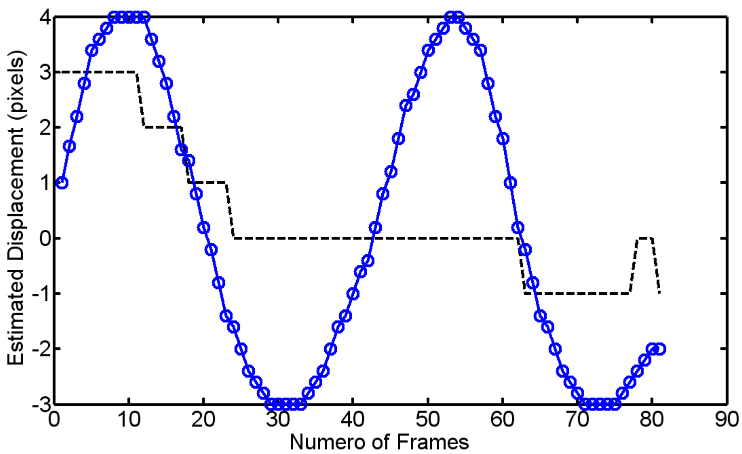

Figure 2 : Relative pixel displacement along X (black dot line) and Y (blue circle in continuous line) for the first pixel detected motion. Y has an harmonic form as the bridge is excited in bending (Y axis).

Future works will focus on passing through this hypothesis in developing a correcting factor of Y displacement function of relative X displacement. Neural networks should be able to reconstruct missing data from neighbour value interpolation using their good generalization abilities even in non linear problem.

The proposed validation is a bridge monitoring using real video data. We extract the 3 dynamic parameters from displacement signals estimated with optical flow. If this work is done regularly, specialists of the bridge could notice the change in these parameters and allow an easy structural health monitoring of the structure. This groundwork will permit to develop several enhance tools (accurate signal reconstruction and ambient excitation) to adapt the method to " real structure" monitoring. Global dynamic parameters of the bridge are estimated from FRF using classical frequency method called Rational Fraction Polynomial (RFP) and are listed in table 2.

E(f)	*σ (f)*	*E(ξ)*	*σ (ξ)*
0.48 (Hz)	*1E-2*	*4.7 (%)*	*1E-2*

Table 2: Estimated mean E and standard deviation *σ* for frequency f and damping ξ

The mode shape of the second harmonic is estimated (figure 3) using the fact that the unknown human loading excitation is very close from the second harmonic ($E(j\omega)$ of Equation 1 is maximal). So the only error due to peak picking and RFP method is that the mode is not scaled. We also fit experimental data with the analytical equation of the dynamic motion of a beam using least square method with very good correlation ($R^2 = 0.9919$). A this step further works can be done because of unknown information (geometrical characteristics of the bridge).

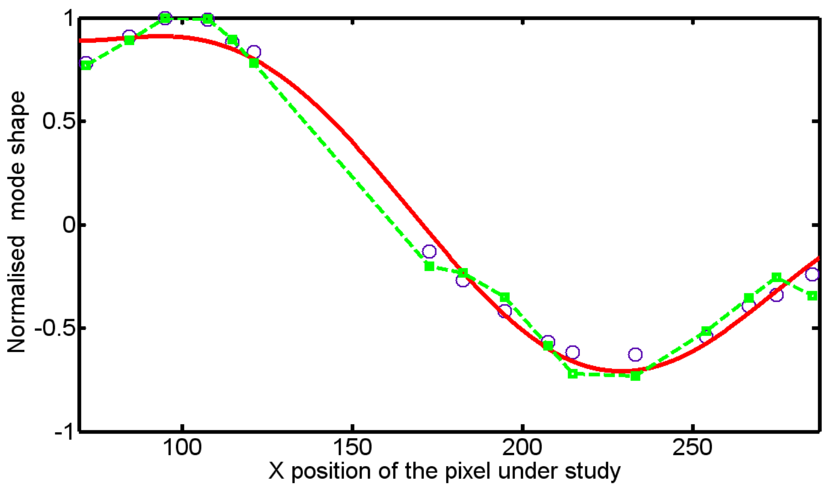

Figure 3: Estimated mode shape from peak picking method (blue circle), RFP method (dot green line with square) and analytical mode shape (red continuous line).

In our experimental results the spatial sampling is not regular (due to complex zone around the human excitation [120-160 pixels]), so in perspective this zone could not be used with curvature damage detection algorithms. One of other limitations is that the influence of the camera viewpoint and calibration is not taking into account in our study. Moreover the extracted mode shape is not scaled due to the fact that human harmonic loading (unknown force) has excited the second harmonic of the bridge. Finally the vertical sensitivity will be low due to the size of the deflection compared to the length of the bridge. Nevertheless the main interest of our method is that no targets need to be placed on the structure and also no time consuming computation is needed (for real time applications).

From video motion estimation to dynamic monitoring

An excellent survey [2] introduces several classes of optical flow estimation methods and compare the performance of them . There are several benefits of using high frame rate sequences. First, as frame rate increases, the intensity values along the motion trajectories vary less between consecutive frames when illumination level changes Another important benefit is that as frame rate increase the captured sequence exhibits less motion aliasing. For example, when motion aliasing occurs a wagon wheel might appear to rotate backward even to a human observer when seen on TV. To recover the original continuous spatio-temporal video signal from its temporally sampled version, it is clear that the temporal sampling frequency (or frame rate) fs must be greater than $2Bt$ (Equation 2) in order to avoid aliasing in the temporal direction (Nyquist criteria). If we assume global motion with constant velocity vx and vy (in pixels per standard-speed frame) and spatially band limited image with Bx and By as the horizontal and vertical spatial bandwidths (in cycles per pixel), the minimum temporal sampling frequency fs (in cycles per speed frame) to avoid motion aliasing is given by:

$$fs = 2Bt = 2Bx.vx + 2By.vy \qquad (2)$$

The assumptions of optical ideal conditions and ideal blur filter have been done here. Typical high speed camera uses a state-of-the-art CMOS sensor that records images at 1000 FPS (ore more) at 1280×1024 pixel resolution (ore more). Our video data resolution is 320×240, we succeed to initialize the optical flow with 16 targets on a studied length of 260 pixels. So we propose to introduce the Pixel Spatial Resolution (SPR in pixels). We introduce in Equation 3, 2 empirical values for low ($PSR_o \approx 16$) and high ($PSR_m \approx 64$) optical flow performance results:

$$SR_o = \frac{PSR_o}{L} \text{ and } SR_m = \frac{PSR_m}{L}. \qquad (3)$$

The figure 4 illustrates the variation of the spatial resolution function of the beam length L. At a constant image resolution the spatial resolution decreases with the beam length (the number of targets is constant). Using beam like structure of one meter length with the best optical flow results, (SR_m) the spatial resolution is closed to LDV resolution. So we can assess small structure using classical algorithm of mode shape based damage detection [4,5,8,9] and also use the results of previous works [8] to estimate the damage size. These methods use the curvature mode shape [4,8] properties to find relationship between optimal sampling data and measurement noise. In video processing, the less objectionable noise is the random noise usually much more difficult to remove without degrading the image than fixed pattern noise and banding noise.

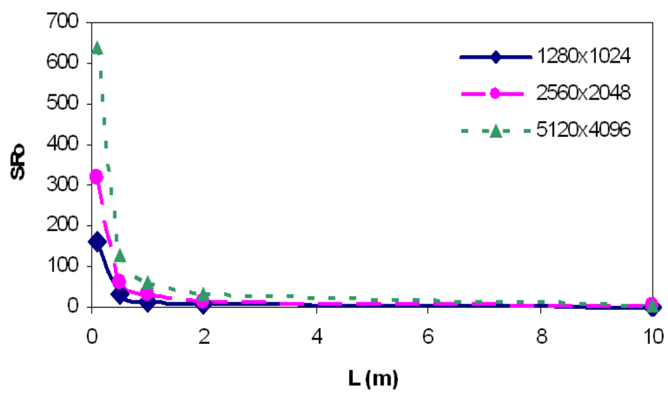

Figure 4: Minimal spatial resolution (SR_o) versus length of the studied beam (L)

Conclusion

Our paper tries to establish that computer vision methods are able using Lukas-Kanade optical flow algorithm to extract reliable dynamic parameter. We proposed a validation software (under openCV) to extract the second mode, frequency and damping of a bridge excited by harmonic loading. High speed camera and robust optical setup will allow laboratory works to monitor a large structure using mode shape based damage detection method. Making the assumption of high contrast and high vertical resolution (to obtain sufficient deformation) our method coupled with operational modal analysis could also be used to monitor real structure like bridge under ambient excitation. Finally computer vision method are less expensive and more convenient for field instrumentation than laser Doppler vibrometer, and piezo-accelerometer with the goal of a continuous monitoring of large structure (frequency bandwidth of several hundred of Hz). Keeping in mind the fact that accuracy and low noise measurement are significant parameters to succeed in locating damage, further works should focus on comparing computer vision to vibrometer laser performances in a laboratory experiment. It will be also interesting to obtain high resolution mode shapes from ambient vibration measurement and synchronized multiple camera.

References

[1] J.K. Aggarwal, and N. Nandhakumar, (1988). On the computation of motion from sequences of images - A review Proceedings of the IEEE, 76(8):917-935.

[2] J.L. Barron, D.J. Fleet, and S.S. Beauchemin, Performance of Optical Flow Techniques, International Journal of Computer Vision, vol. 12(1), pp. 43–77, February 1994.

[3] J.Y. Bouguet. Pyramidal Implementation of the Lucas Kanade Feature Tracker, openCV documentation.

[4] S. W. Doebling, C. R. Farrar, M. B. Prime, and D. W. Shevitz, Damage Identification and Health Monitoring of Structural and Mechanical Systems From Changes in their Vibration Characteristics: A literature Review, Los Alamos National Laboratory report LA-13070-MS

[5] J.-C. Hong, Y.Y. Kim, H.C. Lee and Y. W. Lee, Damage detection using the Lipschitz exponent estimated by the wavelet transform: applications to vibration modes of a beam, International Journal of Solids and Structures, Volume 39, Issue 7, April 2002, p 1803-1816.

[6] Lim, S.; Apostolopoulos, J.G.; Gamal, A.E., Optical flow estimation using temporally oversampled video, Image Processing, IEEE Transactions on , vol.14, no.8pp. 1074- 1087, Aug. 2005

[7] B.D. Lucas and T. Kanade, 1981, An iterative image registration technique with an application to stereo vision. Proceedings of Imaging understanding workshop, pp 121--130.

[8] J. Morlier, F. Bos, P. Castera, Benchmark of damage localisation Algorithms using mode shape data, Key Engineering Materials, 293–294 (2005), pp. 305–312.

[9] J. Morlier, F. Bos and P. Castéra, Diagnosis of a portal frame using advanced signal processing of laser vibrometer data, Journal of Sound and Vibration, 297, Issues 1-2, (2006), pp 420-431.

[10] P. Olaszek, Investigation of the dynamic characteristic of bridge structures using a computer vision method. Measurement 1999;25:227–36.

[11] S. Patsias and W.J. Staszewski, Damage detection using optical measurements and wavelets, Vol 1, Structural Health Monitoring, Sage Publications, Beverley Hills, CA (2002) pp. 5–22.

[12] B. Peeters and G. De Roeck, Stochastic System Identification for Operational Modal Analysis: A Review, J. Dyn. Sys., Meas., Control 123, 659 (2001)

[13] U.P. Poudel, G. Fu and J. Ye, Structural damage detection using digital video imaging technique and wavelet transformation, Journal of Sound and Vibration 286 (2005), pp. 869–895.

[14] L. Zimet, M. Shahram, and P. Milanfar, An adaptive framework for image and video sensing, Proc. SPIE Int. Soc. Opt. Eng. 5678, 156 (2005)

[15] Information on http://www.intel.com/technology/computing/opencv/