Title	Smartphone based parameter estimates of a dynamic oscillator using high-speed video imaging and incremental discriminating colour learning
Authors(s)	Zeimys, Modestas, Pakrashi, Vikram, O'Byrne, Michael
Publication date	2017-07-20
Publication information	Zeimys, Modestas, Vikram Pakrashi, and Michael O'Byrne. "Smartphone Based Parameter Estimates of a Dynamic Oscillator Using High-Speed Video Imaging and Incremental Discriminating Colour Learning." IEEE, July 20, 2017. https://doi.org/10.1109/ISSC.2017.7983640.
Conference details	2017 28th Irish Signals and Systems Conference (ISSC) Killarney, Ireland, 20-21 June, 2017
Publisher	IEEE
Item record/more information	http://hdl.handle.net/10197/10342
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Publisher's version (DOI)	10.1109/ISSC.2017.7983640

Smartphone based Parameter Estimates of a Dynamic Oscillator using High-Speed Video Imaging and Incremental Discriminating Colour Learning

Modestas Zeimys
Dynamical Systems and Risk Laboratory (DSRL), School of Mechanical and Materials Engineering, University College Dublin, Ireland
modestas.zeimys@ucdconnect.ie

Vikram Pakrashi
Dynamical Systems and Risk Laboratory (DSRL), School of Mechanical and Materials Engineering, University College Dublin, Ireland
vikram.pakrashi@ucd.ie

Michael O'Byrne
Dynamical Systems and Risk Laboratory (DSRL), School of Mechanical and Materials Engineering, University College Dublin, Ireland
michael.obyrne@ucd.ie

***Abstract*—Image-based systems are increasingly being used for Structural Health Monitoring (SHM) applications. Video-based motion tracking algorithms can be used to analyse dynamic responses characterised by low frequencies, large deflections and low damping ratios. The advantages of image processing over other methods include the ability to track multiple points on a structure, its scalability, and its ease of use. Standard video acquisition devices are limited in their ability to assess dynamic responses and identify natural frequencies or damping ratios of structures due to the relatively low sampling rate, or frame rate. As such, there becomes a need to use video cameras that possess the ability to record at high frame rates – a feature that is becoming increasingly common on modern smartphones. This paper demonstrates how such video cameras can be used to estimate natural frequencies and viscous damping ratios of structures by considering a Single Degree of Freedom (SDOF) linear system undergoing free vibrations. The slow-motion feature on a Nexus 6P Smartphone was used to capture the dynamic response of the vibrating system. The video was assessed by an Incremental Discriminative Colour Tracking (IDCT) algorithm which tracked the position of points on the system, from which the natural frequency and damping ratio could then be extracted. The results were compared to a reference accelerometer and theoretical estimates. This paper acts as an evidence base for the evolving capabilities of smartphone based monitoring, and ultimately, shows that smartphones have value as a tool for the cost-effective assessment of structures.**

Keywords—Smartphone; high-speed video; system identification; dynamics; Incremental Discriminative Colour Learning; Structural Health Monitoring (SHM)

I. Introduction

Structural Health Monitoring (SHM) is one of the key engineering challenges for the built infrastructure [1]. Successful SHM can lead to increased safety and reduced cost of infrastructure, which often form the lifelines of society [2]. SHM is a burgeoning, dynamic field, that is strongly shaped by new technologies. Consequently, it is important to develop experimental evidence bases around these emerging technologies and methods.

A. Structural Health Monitoring and Image Processing

While visual data is almost always captured as part of the structural assessment regime, the exploitation or utilisation of images/videos at a quantitative level is still at a nascent stage, especially in relation to analysing the dynamic behaviour of structures. Instead, engineers often rely on conventional methods such as accelerometers, harvesters and strain gauges to acquire quantitative measurements. These conventional methods can monitor a single point at a time on a given structure. Image processing methods, on the other hand, are potentially capable of analysing full-field behaviour. Moreover, measurements can be obtained in a non-contact manner leading to system identification [3].

Image processing techniques are used for a wide array of applications in engineering and SHM, such as for damage detection [4]. Video analysis may be viewed as an extension to standard image analysis methods as video contains temporal information in addition to the visual information. This opens up new possibilities and application areas in SHM, especially in relation to dynamic systems. Video analysis enjoys many of the same benefits as image analysis. On a software level, it is possible to draw on a broad range of existing algorithms, such as real-time video tracking [5], and adapt them for SHM purposes. On a hardware level, video devices are readily available and require only minimal training in their operation, unlike other competing tools, such as laser doppler vibrometers, which are comparatively expensive and cumbersome [6].

Experimental evidence around parameter estimation techniques using video imaging can help develop prognostic tools for built infrastructure - a wide range of which can be represented as Single Degree of Freedom (SDOF) systems for various investigation, analysis, monitoring and assessment purposes. Estimation of natural frequency and damping are particularly relevant in such cases. Video image processing has recently been utilised for characterising the natural frequency of an iconic pedestrian bridge in Ireland and it showed that it was possible to distinguish the movements of pedestrians and bicycles from the natural frequency of the bridge using a wavelet packet transform based energy envelope, even when the natural and the excitation frequencies were very close [7]. This paper presents an example where the natural frequency and damping ratio of an SDOF system are estimated using high-speed video image processing in a laboratory environment and using a smartphone.

B. High-Speed Cameras in Image Processing

Accelerometers measure at a single point on the host structure but can have a very high sampling rate. Wireless sensor networks, consisting of multiple accelerometers attached at different points on a structure, extend the sensing capabilities but are expensive and time-consuming. In contrast, image processing provides high spatial resolution and simultaneous measuring of multiple points. One of the main limitations associated with image processing is the sampling rate, which depends on the shooting frequency of the camera used. For most affordable digital cameras, the shooting rate is typically limited to 30-60 Hz [8]. This introduces the need for high-speed cameras. Traditional high-speed cameras are costly and generate excessively large file sizes in a short period of time. Recent smartphones have now created a possibility of taking video images at higher speed, but are not well compared against established benchmarks. For the purposes of this experiment, the slow-motion function of a Nexus 6P smartphone was used to capture the motion of the SDOF tested in this paper. Smartphones are ubiquitous and readily available, with a large portion possessing the slow-motion video functionality. They are cheaper and easier to use than standard high-speed cameras. A comparison of such phone based system against conventional measurement devices does not yet exist in the context of video image based identification of parameters of dynamic systems.

While high-speed cameras have been utilised for image processing applications in the past, there has not been extensive research into their limitations. More specifically, there is scope to improve understanding around the sampling frequency and the tradeoff between sampling rate and the quality of the image and how they relate to image processing and the ability of a motion tracking algorithm to track an object on a vibrating structure [9]. One of the main applications for high-speed cameras in image processing is Direct Image Correlation (DIC), which is similar to stereoscopic vision, where it effectively relies on observing a tracked object from two points to ascertain its position in space [10]. This information can then be used to extract the vibration mode shapes [11]. However, the set-up is complicated and requires a significant amount of custom made components, which impedes this method. This paper explores some of the tradeoffs associated with using high-speed cameras for image processing, with a particular focus on trying to characterise vibrating systems.

C. Objectives

This paper demonstrates the possibility of using high-speed video image processing using smartphones as a suitable method for SHM. Its performance is compared to that of a high-quality accelerometer for estimating the natural frequency and damping ratio of an SDOF dynamical system using its free vibration response. The methodology section outlines the experimental set-up used for this experiment, the camera set-up, and the image processing algorithm. The results from image processing and from the accelerometer are presented and compared with one another, along with the theoretical values of the system. The conclusion section provides the context around this work in terms of its impact on SHM and how image processing might mature this domain further, especially with the help of new generation smartphones.

II. METHODOLOGY

This section consists of four parts related to the experiment. The first part describes the experimental set-up, the relevant camera settings, and the accelerometer set-up. The second part describes the SDOF system under investigation along with its mathematical model. The third part outlines the video tracking algorithm that was used and how it operates. The fourth part outlines the limitations associated with image processing as a vibration assessment tool.

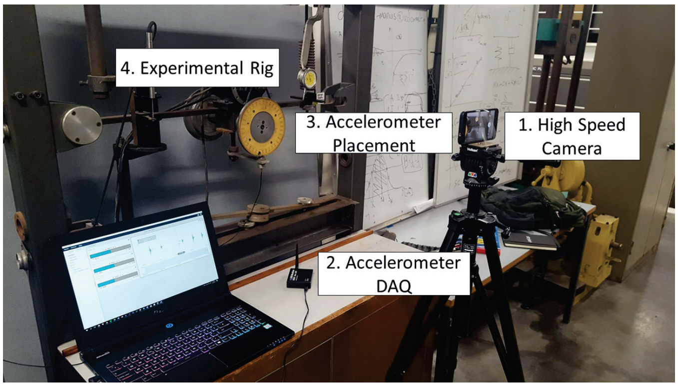

Fig 1. Experimental Set-up

A. Experimental Details of High-Speed Video Imaging

Figure 1 presents the setup of a high-speed camera. Originally a Phantom v5.1 camera was going to be used for the experiment. However, a much cheaper and simpler alternative was found in the slow-motion camera shooting application of a Nexus 6P smartphone. The Phantom v5.1 is able to shoot video up to 1200 FPS, which would provide a very high sampling frequency and this would allow systems with higher vibration frequencies to be evaluated and characterised. This was not necessary for the current experiment and a wide range of built infrastructure are characterised by dynamic responses with frequencies well within the limits of what could be observed using the smartphone, even after considering Nyquist criterion. On the other hand, the evaluation of new smartphones also addresses the ongoing uncertainty around whether and to what extent cheaper sensors can be used for quantitative purposes. Using traditional high-speed cameras also uses very large amounts of Hard Disk Drive (HDD) space and this leads to a significantly long time for processing. These drawbacks are largely offset using a smartphone. One of the other main reasons the slow-motion feature of a Nexus 6P Smartphone was used, is because it shoots in colour, whereas the Phantom v5.1 camera shoots only in black and white.

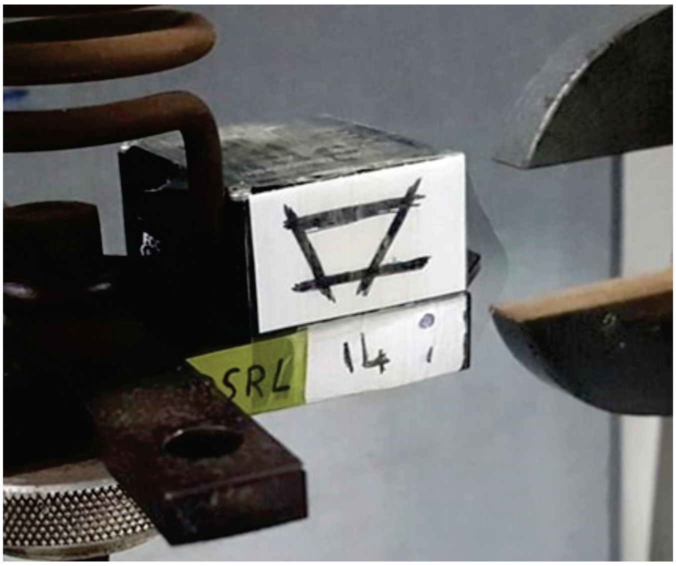

Fig 2. Placement of the accelerometer

B. Set-up of the Single Degree of Freedom (SDOF) System

The SDOF system being characterised in this experiment was a rigid beam hinged on one side with a damper and spring attached at distances l_1 and l_3 respectively (Figure 3).

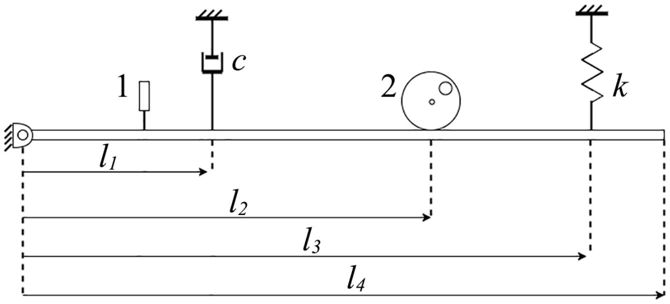

Fig 3. Schematic of the experimental SDOF system

Figure 4 presents the free body diagram of the SDOF system to illustrate the force and moment balance.

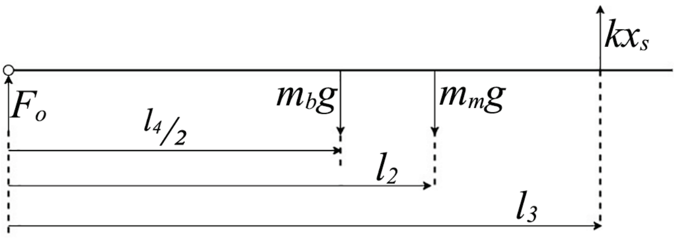

Fig 4. Free body diagram of the experimental SDOF system

The variables presented in the free-body diagram of the beam presented in Figure 4 are:

m_b — beam mass (kg)
m_m — motor mass (kg)
x_s — static spring deflection (m)
c — damping coefficient (N.m.s^{-1})
k — spring stiffness (N.m^{-1})
I_0 — moment of inertia (Kg.m^2)

Static equilibrium of force at hinge (F_0), stiffness and gravitational effects is given as

$$F_0 + kx_s = m_b g + m_m g \quad (1)$$

where the remaining parameters are explained in Figure 4. Considering moment equilibrium about the hinge yields

$$m_m g\left(\frac{l_4}{2}\right) + m_m g l_2 = kx_s l_3 \quad (2)$$

Consideration of small angular deflection (Θ<10°) at the end, as per Figure 5, leads to

$$\sum M_0 = I_0 \ddot{\theta} \quad (3)$$

$$I_0\ddot{\theta} = -cl_1\dot{\theta}l_1 + m_b g\left(\frac{l_4}{2}\right) + m_m g l_2 - k(x_s + l_3\theta)l_3 \quad (4)$$

Substituting Eq. 2 into Eq. 3

$$I_0\ddot{\theta} + cl_1^2\dot{\theta} + kl_3^2\theta = 0 \quad (5)$$

which can be related to the standard form of free vibration of SDOF systems

$$m\ddot{x} + c\dot{x} + kx = 0 \quad (6)$$

where m is the mass of the SDOF system, c is damping and k is stiffness or

$$\ddot{x} + 2\zeta\omega_n\dot{x} + \omega_n^2 x = 0 \quad (7)$$

where ζ is damping ratio, ω_n is the natural frequency in Hz and the damping ratio is defined as

$$\zeta = \frac{c}{c_c} \quad (8)$$

where c_c is the critical damping coefficient.

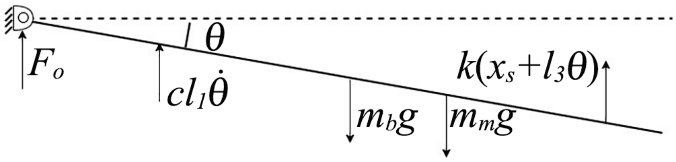

Fig 5. Small rotations at the end of the beam

The damping ratio can be found from the logarithmic decrement (δ) of the peaks of free vibration response. In the experiment, considering the amplitude of a vibrating point to be X_0 and the amplitude of the n^{th} cycle, X_n and acknowledging transient exponential decay, we obtain $\frac{X_0}{X_n} = e^{n\delta}$, which can be written as:

$$\delta = \frac{\ln(X_0/X_n)}{n} \quad (9)$$

which can then be related to the estimate [12], as per:

$$\delta = \frac{2\pi\zeta}{\sqrt{1-\zeta^2}} \quad (10)$$

Rearranging this expression, and considering low sub-critical damping, typical for such vibrating structures under consideration, gives

$$\zeta = \frac{\delta}{\sqrt{4\pi^2 + \delta^2}} \approx \frac{\delta}{2\pi} \quad (11)$$

The approximation is accurate when δ<<1. Using this value of ζ, the damping coefficient c and the damped natural frequency (f_d) can be determined, using $f_d = f_n\sqrt{1-\zeta^2}$.

III. IMAGE PROCESSING ALGORITHM

The Incremental Discriminative Colour Learning (IDCT) algorithm used in this experiment tracks a given object in a frame by distinguishing it from its surroundings in each successive frame. The algorithm is initialised by first turning the video being processed into a series of images, with each frame being a different image. Figure 6 presents the object tracked by the algorithm in the form of a high-contrast point.

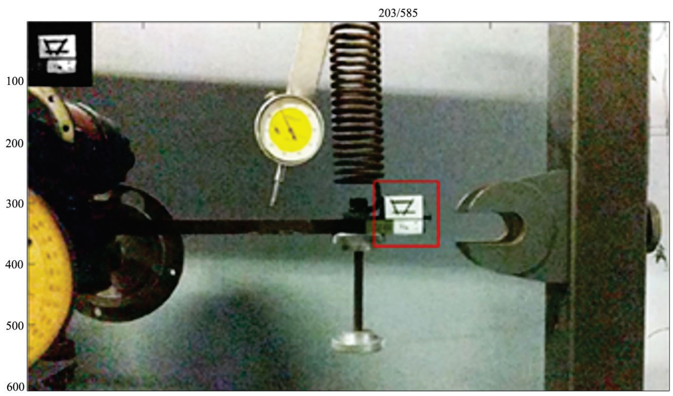

Fig 6. Object tracked by the algorithm shown in a red square

With this algorithm, object tracking begins by approximately selecting an object in the first frame. The object must stand out from the background for best results. In this experiment, a high contrast point was created by attaching a sticker to the accelerometer. A surrounding area is computed automatically so that if the motion of the object being tracked is considerable it is not lost from frame to frame. First, a model of the object that is being tracked is developed by the algorithm. The model is represented in terms of RGB (Red Green Blue) histograms. Subsequently, the object from the background in subsequent frames is accurately identified. This algorithm was chosen since it relies on colour to locate the object of interest, and can thus capitalise on the full-colour video recorded by the Nexus 6P. The discriminative class of image processing algorithms uses the classifier to distinguish the object from the surrounding background. The algorithm is also capable of handling visual drift effectively when compared to five other state of the art image processing algorithms, which makes it appealing for assessing vibration based problems [13]. The schematic of the algorithm is presented in Figure 7.

A. Object Modeling

The object is continuously built in this algorithm based on discriminative 3D joint RGB histograms of the object as well as the background. The modelling begins with the algorithm building 3D RBG histograms of the object that was specified by the user as well as the automatically computed area around the object.

B. Detection and Localisation

The positive log-likelihood ratio provided in the object modelling phase of the algorithm is then used in object detection, and all the mean-shift on the confidence map is used for object localisation. Steps are described in the following subsections.

1) Detection

The positive log-likelihood ratio L_s provides a confidence map, $M(x_i, y_i)$ from the object region, $I(x_i, y_i, c_j)$ i. e.,

$$L_s : I(x_i, y_i, c_i) \rightarrow M(x_i, y_i) \quad (12)$$

where (x_i, y_i) is the pixel location in the image coordinate. The index i ranges from 1 to N, where N is the total number of pixels in the object region, both the actual object and the automatically generated area around the tracked object. c_j is the colour channel of the image. Index j varies from 1 to 3 for the RGB colour channels. The resulting map is a confidence map image, and its pixels with higher values are more likely to belong to the object being tracked. The result of this procedure is shown in Figure 8.

2) Localisation

The localisation for the object in the next frame starts in the centroid of the confidence map in the current frame. This is acceptable if the movement of the object is not overly large, in that case, the mean-shift object localisation on the confidence map of the object provides satisfactory performance.

To account for appearance variation of the object, it is the object model is adapted to recent observations. Once the object location at the current frame is provided by the mean-shift, the positive log-likelihood ratio L_p^t is computed and used to update the previous object model. The algorithm can gradually learn the colour schematic of the with each successive frame, effectively becoming more accurate with each iteration. Without the update to the object model, the confidence map degrades gradually. However, the IDCT algorithm learns the new colours of the object and provides a more precise confidence map of the object.

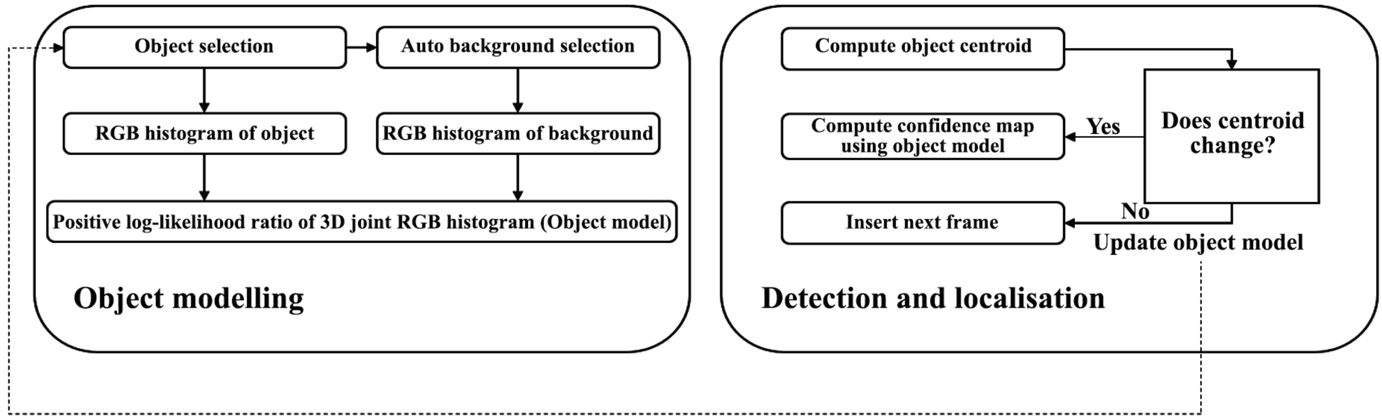

Fig 7. Architecture of the Incremental Discriminative Colour Learning (IDCT) algorithm

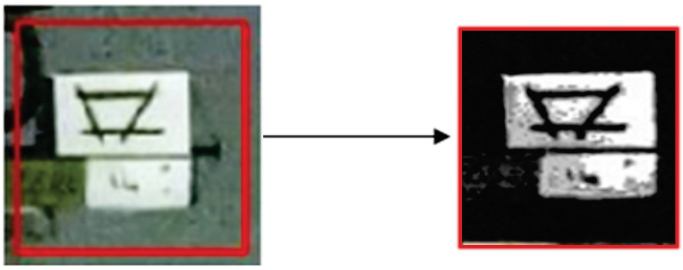

Fig 8. Confidence map of the object tracked

3) Tracking Challenges

There are challenges and limitations that need to be considered when using video motion tracking for a moving point in any video. The most prominent issue that may be encountered is the drift or the complete loss of the point being tracked. This can occur for several reasons, including temporary occlusions in the video, luminous complexities, shadows, or light reflection that may obstruct the object being tracked. These issues can be mitigated if several high contrast points are picked on the point of interest on the structure being evaluated. Another important factor to consider is the accuracy of the tracking. Even at high resolutions, very minute changes of only a few pixels in the video frames could be lost, which in some cases could result in unobserved vibrations. Despite these challenges, the tracking worked well in our example, as may be noted from the normalized displacement versus time graph in Figure 9. As a reference, the output from the accelerometer is displayed in Figure 10.

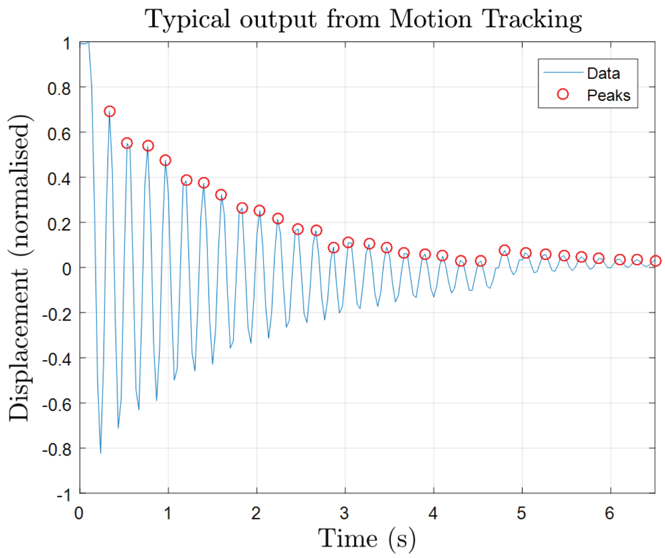

Fig 9. Transient responses of the SDOF system obtained from image processing

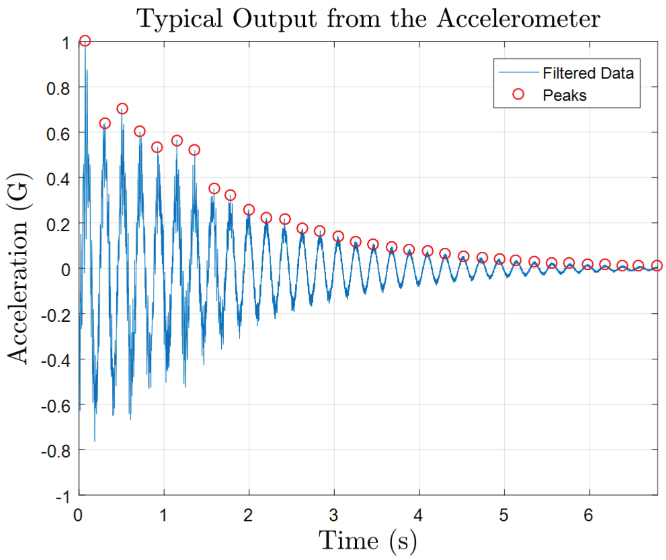

Fig 10. Transient responses of the SDOF system obtained from the accelerometer

Table 1. Comparison of experimental results

	Sensor Type	Test 1	Test 2	Test 3	Test 4	Test 5	Average	% Discrepancy
Natural Frequency (Hz)	Accelerometer	4.75	4.76	4.76	4.77	4.76	4.76	2.68
	Image Processing	4.56	4.56	4.79	4.65	4.62	4.63	
Damping Ratio	Accelerometer	0.023	0.024	0.023	0.025	0.024	0.024	13.37
	Image Processing	0.017	0.017	0.021	0.024	0.024	0.021	
Damped Natural Frequency (Hz)	Accelerometer	4.75	4.76	4.75	4.77	4.76	4.76	2.67
	Image Processing	4.55	4.55	4.79	4.64	4.62	4.63	

The logarithmic decrement was calculated by comparing all the positive peaks in the free vibration decay and calculating the logarithmic decrement between every two peaks and then computing the average. The theoretical natural frequency was calculated to be 4.808 Hz and the damping ratio as 4.67% of the critical damping ratio. Detailed results are presented in Table 1. The discrepancy between the accelerometer and the motion tracked values is relatively small and nearly similar across all tests. There is a larger discrepancy between the damping coefficient estimates when compared between accelerometer and motion tracking. This can be explained by the fact that different dynamic responses were being tracked by the two different methods. The accelerometer was observing the acceleration of the beam, whereas the motion tracking algorithm simply tracks the pixel displacement of the object that was specified and consequently for small values, like estimates of damping ratios, the percentage discrepancy tends to be higher. This is in line with variations of such sub-critical damping ratios typically observed.

IV. CONCLUSIONS

This paper shows how motion tracking algorithms can be used in conjunction with high-speed videos obtained from smartphones to estimate the parameters such as natural frequency and damping coefficients of dynamic oscillators to a relatively high degree of accuracy. These parameters serve as indicators of the structure's health. The motion tracking algorithm is successfully applied and validated on an SDOF system undergoing transient vibration and the results compare well with estimates of natural frequency and damping ratio obtained from accelerometer data. The results from these tests show that the video-based motion tracking technique is a convenient, low-cost method for executing quick vibration based assessments of SDOF systems. Moreover, the results underline the effectiveness of smartphone based assessments and provide reassurance that the video quality on these devices is adequate in some cases.

ACKNOWLEDGMENTS

The author wished to acknowledge SFI Centre Marine Renewable Energy Ireland (MaREI) grant no. 12/RC/2302.

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