Observation of tower vibration based on subtle motion magnification

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Abstract: The vibration of the tower will cause fatigue damage of the tower, reduce the bearing performance of the tower, and result partially damage of the tower. It is difficult to implement and maintenance for the traditional contact measurement method. Motivated by this fact, we propose a non-contact method to measure the vibration of the tower. We apply the video subtle motion magnification algorithm to the tower vibration observation. By processing the video sequence of the tower, we can directly observe the tiny movement of the tower using the naked eye without complicated sensor equipment. The proposed method is used Eulerian Video Magnification technology which processes the image as a whole to reduce computational cost and make the processed image real.

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1. INTRODUCTION

The tower is sensitive to wind loads and has a small lateral rigidity. Under horizontal load, it is easy to produce a large horizontal displacement. The vibration of the tower will cause fatigue damage of the tower, tear the bolt holes, loosen the node bolts. It reduces the bearing performance of the tower and results partially damage of the tower. The vibration of tower under wind load is one of the important factors affecting the stability of tower structure. Therefore, the vibration characteristics of the tower should be analyzed when studying the state of the tower structure. Since the vibration status of the tower reflects the health status of the tower, it's necessary to measure vibration of the tower by some method. The traditional method is measured by contact sensors installed on the tower. However, the contact sensors are susceptible to environmental interference. And the sensor attached to the measured object changes the properties of the measured object, thus affects the vibration mode and frequency measurement accuracy of the measured object.

Non-contact measurement method can overcome these defects, so we focus on non-contact technology to measure tower vibration. Non-contact measurement obtains information about the object to be measured without touching the object, which is usually based on optical, electrical, magnetic, and other techniques. Typical non-contact measurements include laser trigonometry, eddy current method, ultrasonic measurement, and machine vision. In this paper, we measure the vibration of the tower using a non-contact technology based on machine vision. That is, the image acquired by the image acquisition device is processed by the computer to complete the measurement of the vibration, strain and mechanical properties of the object.

The vibration of the tower is so small that it cannot be directly observed by the naked eye and traditional machine vision methods. Therefore, we need a method of amplifying subtle motion, which is similar to a "motion magnifier" or "motion microscope", which can amplify small movements invisible to the naked eye in a video sequence.

The motion microscopic technique was first proposed by Liu et al. (2005). It is a subtle motion magnification technique based on the Lagrangian approach. The steps of this method are as follows. First, all input images are calibrated onto a reference frame which is a global affine motion estimated by matching on a stable set of feature points. Second, the motion-related (not necessarily the same) objects are clustered to combine the motions with common causes. Third, a dense optical flow field is interpolated for each pixel. Fourth, the image is segmented according to the likelihood of motion possibilities and spatial connectivity. Finally, the displacement is enlarged and the image is rendered. The Lagrangian motion magnification technique can magnify motion in the visual effect, but the method relies on the previous clustering and segmentation processing, and the optical flow analysis of the image is required. So the calculation amount is large, and it is difficult to perform real-time processing on the image.

Eulerian Video Magnification (EVM) was proposed by Wu et al. (2012). Eulerian method is a way to describing fluid motion and different from Lagrangian method. It defines fluid as a correlation function of spatial position and time, that is, the distribution of variables (such as velocity, density, etc.) in the flow field over time. Inspired by this method, Eulerian motion magnification technique describes the video sequence as a function of time and space to observe the change in intensity in any spatial location over time. The core of the method is to capture information about the small motions in the video sequence by analysing the intensity of the arbitrary spatial
position over time, and to amplify the changes in the particular frequency of interest. It not only magnifies color variation, but also amplifies low-amplitude motion. Eulerian video magnification technology reduces calculations and improves real-time performance. Therefore, it has attracted the attention of many scholars and further research and improvement.

EVM is only good at low-amplitude motion magnification, not at large-scale motion magnification. Zhang et al. (2017) presented an improved method to make it do well in large-scale motion magnification. It amplifies the deviation of changes instead of the temporal changes which is different from EVM.

2. EULERIAN VIDEO MAGNIFICATION

Eulerian Video Magnification (EVM) processes the video in the time domain and the spatial domain, and magnifies the small motion in the video based on the first-order Taylor series difference approximation.

Eulerian Video Magnification relies on a differential approximation, which is also the basis of an optical flow algorithm. The following describes how to use a first-order Taylor series to amplify motion in a video sequence.

In order to more clearly describe the color or grayscale variation of a position over time, the simple case of one-dimensional translational motion is firstly analyzed, and the analysis can be directly applied to the two-dimensional translational motion. Let \( I(x,t) \) denote the image intensity at position \( x \) and time \( t \). Let the initial time is 0, and the intensity of the initial moment at position \( x \) is represented by Eq.1.

\[
I(x,0) = f(x) \quad (1)
\]

When there are motions in a series of video images, the images change over time, and the change signal generated by the motion can be represented by the displacement function \( \delta(t) \) which is the displacement of time \( t \). The intensity \( I(x,t) \) of position \( x \) and time \( t \) can be expressed as

\[
I(x,t) = f(x + \delta(t)) \quad (2)
\]

According to the first-order Taylor series expansion

\[
f(x) = f(x_0) + \frac{f'(x_0)}{1!}(x - x_0) + R(x) \quad (3)
\]

Where

\[
R(x) = \frac{f''(x_0)}{2!}(x - x_0)^2 + \cdots + \frac{f^{(n)}(x_0)}{n!}(x - x_0)^n + R_n(x),
\]

when \( (x-x_0) \) is small enough, it can be ignored.

Extend \( f(x+\delta(t)) \) with a first-order Taylor series at \( x \) when ignored the \( R(x) \)

\[
I(x,t) = f(x) + \frac{\partial f(x)}{\partial x} \delta(t) \quad (4)
\]

Comparing Eq.4 with Eq.1, we can see that the part of the signal change is \( \delta(t)\partial f(x)/\partial x \).

The change signal \( B(x,t) \) is extracted by the low pass filter filtered out the original signal.

\[
B(x,t) = \frac{\partial f(x)}{\partial x} \delta(t) = I(x,t) - I(x,0) \quad (5)
\]

The change signal is magnified by a factor of \( \alpha \), and then added to the original signal to compose the motion-magnified signals.

\[
\tilde{I}(x,t) = I(x,t) + \alpha B(x,t) \quad (6)
\]

Combining of Eq.4, Eq.5 and Eq.6, we have

\[
\tilde{I}(x,t) = f(x) + (1 + \alpha)\delta(t)\frac{\partial f(x)}{\partial x} \quad (7)
\]

Expand the synthesis of the motion-magnified signals \( f(x+(1+\alpha)\delta(t)) \) by a first-order Taylor series at \( x \)

\[
f(x + (1 + \alpha)\delta(t)) = f(x) + (1 + \alpha)\frac{\partial f(x)}{\partial x} \delta(t) \quad (8)
\]

Comparing Eq.7 and Eq.8, and we can find

\[
\tilde{I}(x,t) = f(x) + (1 + \alpha)\delta(t) \quad (9)
\]

It shows that the spatial displacement \( \delta(t) \) of the partial image \( f(x) \) at time \( t \) can be amplified to a multiple of \( (1+\alpha) \) by amplifying the variation signal extracted by the first-order Taylor series difference approximation. The process of generating motion amplification using approximate difference is shown in Fig. 1.

![Fig. 1. The schematic of First-order Taylor series difference approximation](image)

When the motion is large, the approximation of the first-order Taylor series expansion becomes inaccurate. According to Taylor series expansion:

\[
f(x) = f(x_0) + \frac{f(x_0)}{1!}(x-x_0) + \cdots + \frac{f^{n}(x_0)}{n!}(x-x_0)^n + R_n(x)
\]

where \( R_n(x) \) is Taylor remainder.

Let the \( f(x) = \cos(\alpha x) \) for the signal of the spatial frequency \( \omega \), and \( \beta = 1 + \alpha \) for the multiple of the amplification, where \( \alpha \) is the amplification factor.

The motion-magnified signal \( f(x + \beta\delta(t)) = \cos(\alpha x + \beta \alpha x) \) is approximated by first-order Taylor series at \( \alpha x \), that is
\[ \cos(\alpha x + \beta \omega t) \approx \cos(\alpha x) - \beta \omega \delta(t) \sin(\alpha x) \]  
(11)

And according to the addition law of the cosine
\[ \cos(a + b) = \cos(a)\cos(b) - \sin(a)\sin(b), \]  
we have
\[ \cos(\alpha x + \beta \omega t) = \cos(\beta \omega \delta(t)) - \sin(\alpha x)\sin(\beta \omega \delta(t)) \]  
(12)

Compare the approximation of the first-order Taylor series expansion eq.11 and the expansion of the cosine by the addition lay eq.12, we have the following approximation.
\[ \cos(\beta \omega \delta(t)) = 1 \]  
(13)

\[ \sin(\beta \omega \delta(t)) = \beta \omega \delta(t) \]  
(14)

Let the error of the approximation is allowed within 10%. The sine term leads the approximation and \( \sin(\alpha x) = 0.9x \) when \( x = \frac{\pi}{4} \), this give \( \beta \omega \delta(t) \leq \frac{\pi}{4} \). And for the spatial wavelength \( \lambda = \frac{2\pi}{\omega} \), we have
\[ (1 + \alpha)\delta(t) \leq \frac{\lambda}{8}. \]  
(15)

Eq.15 provides the reference range of the amplification factor \( \alpha \), which depends on the motion signal \( \delta(t) \) and the spatial wavelength of the image \( \lambda \), as shown Fig.1.

![Fig.1](image)

According to the above analysis, the change signal of each pixel is extracted through temporal filter, then the change signal is amplified by the amplification factor, and finally synthesized with the source signal to obtain a motion-amplified image. It is difficult for images to avoid noise, and it is easier to amplify noise when processed separately for each pixel, so spatial filtering is used to reduce noise. And when the spatial frequency is too high, the amplification factor needs to be attenuated, so bands of different spatial frequencies extracted by spatial filters are processed independently.

The framework of the algorithm is shown in Figure 2. The steps of the algorithm are as follows:

1. Spatial Decomposition: the video sequence is decomposed into frequency bands of different spatial frequencies by spatial filters;
2. Temporal Processing: each spatial frequency band is filtered by temporal filter of a particular frequency band to extract the interest change signals;
3. Magnified by \( \alpha \): The change signals in different spatial bands are amplified by amplification factors \( \alpha \);
4. Reconstruction: Synthesize the amplified change signal and the original signal to reconstruct the motion-magnification image, and reconstruct the video.

![Fig.2 EVM Algorithm Framework](image)

Spatial filtering can be done using Laplacian pyramids, Gaussian pyramids, and so on. The temporal filtering can be ideal filter, second-order IIR filter, Butterworth filter, and so on. It should be reasonably selected as needed.

In summary, the Eulerian motion magnification algorithm can be used to magnify the displacement signal and have the characteristics of microscopic motion, and the vibration displacement information of the tower can be observed through video sequence by this way.

3. RESULTS

The Eulerian motion magnification algorithm introduced above was implemented on the QT platform by C++ programming. The video source input in this experiment was taken with a normal camera with a resolution of 1440*1080 and a frame rate of 25 frames per second. It was worth noting that because the camera shakes the experimental results, we fixed the camera as much as possible. In this experiment, we used a tripod to fix the camera. Although it couldn’t completely eliminate the camera shake, the Impact should be reduced as much as possible.

![Interactive Interface](image)

According to the Eulerian motion magnification algorithm, the video will be processed frame by frame after the original video input. The processing steps for each frame are as follows:

1. spatially filtering the image;
2. selecting the appropriate filter type and the cut-off frequency, and temporal filtering on the band of each spatial frequency to extract the change signal that we are interested in;
(3) Selecting the appropriate magnification factor to magnify the changed signal portion;

(4) Reconstruct the image.

In this experiment, we chose the Laplacian pyramid for spatial decomposition. Since the small change in magnification is motion (displacement change), we only down-sample the image for less noise. In order to reduce artifacts and ringing, we choose a second-order IIR filter for temporal filter. The parameters selectable by the user include amplification factor, cut-off frequency of the time domain filter, etc. After inputting these parameters, the video is processed to obtain a video after the micro motion is amplified, and the result is shown in Fig. 4.

![Image](image-url)

Fig. 4. The source and magnified video slices

As shown in Fig. 4, (a) is the first frame of the original input video; (b) is the first frame of the output video after amplification, and the magnification factor is $\alpha=40$; (c) is the first frame of the output video after amplification, and the magnification factor is $\alpha=100$; (d) are the spatiotemporal slices extracted from the input video and the amplified output video in the position of the black thin line as shown in (a), (b), (c). In order to facilitate the observation of the vibration of the tower, we choose the middle part of the tower with a simpler situation to make spatiotemporal slices. The spatiotemporal slices of the input video show straight lines, and it is difficult for us to visually observe the movement of the tower on the X-axis. It is also difficult to observe the vibration of the tower in the input video. In the spatiotemporal slice of the output video processed by the Eulerian motion magnification algorithm, the motion of the tower on the X axis can be observed. And we can easily observe the vibration of the tower in the output video. At the same time, we found that the amplified output image has a large noise. As the magnification increases, the noise becomes more and more obvious. Comparing the spatiotemporal slices of the input and output video, it can be seen that the Eulerian motion magnification algorithm can amplify the small motion for direct observation.

4. DISCUSSION

4.1 Noise

According to the experimental results, we find that as the magnification increases, the amplification of the noise is more obvious. In practical applications, we hope that the magnification is larger to obtain better observation, but the noise will affect the observation. Many scholars have made many efforts to attenuate noise. Wadhwa et al. (2013) proposed Phase-Based Video Motion Processing (PBVM), which amplifies displacement changes by increasing phase, while translational noise can effectively suppress noise, making it possible to support larger Magnification, but also increases the amount of calculation. Since then, the phase amplification algorithm has been continuously improved by many scholars. In order to improve the computational efficiency of continuous image sequences, the fast phase motion amplification algorithm based on pyramid was proposed [Wadhwa et al. (2014); LI LP et al. (2015)]. The algorithm uses the pyramid transform to approximate the sine and cosine signals, which can achieve the similar amplification effect of the same phase motion amplification, and improve the algorithm speed.

4.2 Globality

The basis of the Euler video magnification algorithm is the Eulerian method which processes the image as a whole. Naturally, the algorithm has globality and can capture the change signals of the whole picture. Sometimes globality is beneficial, we can completely observe the changes of the whole object. However, many sensors need to be placed on the measurement object to more completely observe the vibration of the object with traditional contact sensor measurements. It requires the design of the sensors installation location, and optimization algorithms are used, such as Wang Jian (2017).

But sometimes the precise extraction of information is limited by the global presence. The object we want to observe does not completely cover the entire picture. We only care about the change information of the observed part, but there may be change information in other parts of the image, because we...
sometimes have difficulty distinguishing them, it is difficult to extract the change information of the target part.

Since the picture may have large area changes and small area changes, but the global change information is extracted. If all changes are equally amplified, the small area changes may be ignored. Mohamed Elgharib et al. (2015) proposed the Eulerian–Lagrangian hybrid method, the change information of the small area and the large area are separately extracted and amplified by different multiples, which can effectively eliminate the artifacts. B. D. Xue et al. (2019) proposed multi-scale adaptive factors video acceleration magnification, which automatically magnifies by different magnification factor in different spatial scales.

4.3 Automatic parameter determination

For users who are not familiar with the Eulerian video magnification algorithm, it is complicated to select the appropriate parameters. The determination of the appropriate parameters requires multiple attempts, and the parameters may be adjusted for different scenarios. Many scholars have studied the automatic determination of parameters. Sushma et al. (2013) proposed the semi-automated method of semi-automated Magnification of subtle motion in video (SAM) that automatically determines these parameters by using information obtained from the first two frames of video. Lei Lin et al. (2017) proposed the non-stationary subtle motion magnification based on S transform.

5. CONCLUSION

We apply the Euler video amplification algorithm to the vibration observation of the tower, and can intuitively observe the vibration of the tower by amplifying the tiny motion. Based on the experimental results, we discussed the problems of the Euler video amplification algorithm and the research and improvement made on these problems.

REFERENCES

C. Liu, A. Torralba, W.T. Freeman, E.H. Adelson, (2005). Motion magnification, ACM SIGGRAPH, 519–526.
B.D. Xue, S.J. Zheng, W.F. Xue, (2019). Multi-scale adaptive factors video acceleration magnification, Signal Processing: Image Communication, (71) 36–44.
H.Y. Wu, E. Shih, E. Shih, J. Guttag, W. Freeman, (2012). Eulerian video magnification for revealing subtle changes in the world, ACM Trans. Graph. 31 (65).
LEI Lin, L.P. LI, YANG Min, et al. (2017). Non-stationary subtle motion magnification based on S transform, Journal of Computer Applications, 37(5) :1460 – 1465
LI L P, LEI L, SUN S F, et al. (2015). Improved video small motion magnification processing, Computer Engineering and Applications, 51(24) :195 – 200.
M.A. Elgharib, M. Hefeeda, F. Durand, W.T. Freeman, (2015). Video magnification in presence of large motions, Computer Vision and Pattern Recognition, 4119–4127.
N. Wadhwa, M. Rubinstein, M. Frend, W. T. Freeman, (2013). Phase-based video motion processing, ACM Trans. Graph. 32 (1–10).
