LETTER

Video Magnification under the Presence of Complex Background Motions

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SUMMARY We propose a video magnification method for magnifying subtle color and motion changes under the presence of non-meaningful background motions. We use frequency variability to design a filter that passes only meaningful subtle changes and removes non-meaningful ones; our method obtains more impressive magnification results without artifacts than compared methods.

key words: video magnification, complex background motions, frequency variability (FV), Poincaré plot analysis (PPA), frequency variability filter

1. Introduction

The world is full of fascinating and meaningful changes caused by physical and natural phenomena. For example, chest moves in a periodic motion as human breathes [1], and facial color changes slightly accompanying blood circulation [2]. However, these changes are too small to be well seen by the naked eye.

In recent years, video magnification methods [3]–[7] have been proposed, which act as a microscope for visualizing subtle motion and color changes. These methods can be categorized into two cases: Lagrangian and Eulerian approaches. The Lagrangian approach [3] uses optical flow to explicitly estimate motions between frames, and manipulates them to achieve the magnified results. However, the accurate motion estimation is computationally expensive and difficult to make artifact-free at regions of occlusion boundaries and complicated motions. In contrast, Eulerian approaches [4]–[7] decompose video frames into representations, and then manipulate and reconstruct them to obtain the magnified frames, without object tracking. Additionally, according to different types of spatial representation, Eulerian approaches can be further divided into methods based respectively on Laplacian pyramid [4], Steerable filters [5], Riesz pyramid [6] and Deep Learning [7]. These Eulerian techniques have achieved excellent results for magnifying subtle color and motion changes, such as face color changes accompanying blood circulation and small vibrations of a drum. However, these meaningful subtle changes caused by physical and natural phenomena are often mixed with non-meaningful background motions, caused by blinking eyes, moving drumstick, swinging trees or grass, moving pedestrians or vehicles, and so on. Current Eulerian methods can-

not filter out background motions, but magnify them along with meaningful subtle changes. Therefore, they always produce artifacts or blur in magnification outputs, resulting in misleading insights and conclusions for a small world.

To detect and magnify only meaningful subtle changes under the presence of background motions, interest region-based video magnification methods have been proposed [8]–[10]. These methods separate a region of interest (ROI) that to be magnified by user segmentation [8], [9] or saliency detection [10]. They can magnify only meaningful subtle changes if the ROI is prior known or has salient features (e.g. color and pattern) significantly different from background, but require burdensome interventions, such as texture synthesis and image inpainting, to correct transitional zones between magnified and unmagnified regions.

In contrast, acceleration-based methods [11]–[13] dealing with large motions have been proposed to magnify meaningful subtle changes without the aforementioned interventions. Based on the second-order Taylor series expansion, they focus on magnifying the accelerations of changes, instead of conventionally amplifying all changes in time. They can amplify subtle changes both in stationary objects and under large motions, but result in artifacts or blur in magnified videos if background motions exist in the video. This is because they cannot filter out background motions either.

To overcome the negative effects of background motions, this study presents a new video magnification method based on frequency variability, for detecting and magnifying only meaningful subtle color and motion changes. We found that meaningful subtle changes caused by physical and natural phenomena are always periodic motions with a steady peak frequency, while for background motions, their peak frequencies seem to be variable over time due to that background motions always involve complex space-time behavior. We considered that the temporal variability of peak frequency over time, which is called frequency variability (FV), enables us to detect only meaningful subtle changes. To estimate the FV values of subtle changes, we used the Poincaré Plot Analysis (PPA), which is applied in biomedical science to indicate the variability of heart rate (HRV) for predicting the future cardiovascular risk in individuals [14]. Then we utilized the estimated FV values to design a filter (i.e. the frequency variability filter) that passes only meaningful subtle changes and removes background motions. Our method, in which the frequency variability filter is applied to current Eulerian methods [4], [5], creates

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impressive color and motion magnification results without artifacts or blur caused by background motions.

2. Methods

Details of our method are as follows. First, we will show our problem definition and explain why FV is a useful index to distinguish meaningful subtle changes and non-meaningful ones caused by complex background motions. Second, we will describe how we design our frequency variability filter that passes only meaningful subtle changes and filters out non-meaningful ones. Finally, we will show how we apply this filter to current color and motion magnification methods.

2.1 Problem Definition and Frequency Variability

Given an input image signal $I(\mathbf{x}; t)$ at 2D position $\mathbf{x}$ and time t , subtle intensity changes can be calculated by using the expression $B(\mathbf{x}; t) = I(\mathbf{x}; t) - I(\mathbf{x}; 0)$ [4]. Video magnification methods manually select the interest frequency band of $B(\mathbf{x}; t)$ that to be magnified, by using a bandpass filter $BPF(t)$, such as ideal bandpass filter and IIR bandpass filter. Finally, the magnified signal with a factor α is expressed by

$$\hat{I}(\mathbf{x}; t) = I(\mathbf{x}; t) + \alpha(BPF(t) \otimes B(\mathbf{x}; t)), \quad (1)$$

where $\otimes$ is a convolution operator. For details, see [4].

However, $BPF(t)$ only is not enough to ensure that the selected frequency components that to be amplified correspond absolutely to meaningful subtle changes, because non-meaningful ones also have these components. Current methods cannot remove these non-meaningful components, but magnify them along with meaningful ones, thus producing misleading magnification outputs with artifacts or blur.

Our key idea is based on our finding that the peak frequency of the local frequency spectrum of meaningful subtle changes keeps constant for the entire time, while that of non-meaningful ones varies during time intervals due to that background motions always involve complex space-time behavior across pixels. We consider that the temporal variability of peak frequency (i.e frequency variability FV) enables us to distinguish meaningful subtle changes from non-meaningful ones. The interpretation of FV is as follows (Fig. 1).

In order to obtain the peak frequency of the local frequency spectrum of subtle signal $B(\mathbf{x}; t)$, we take the short-time Fourier transform (STFT) of $B(\mathbf{x}; t)$ as

$$STFT(\mathbf{x}; t, f) = \int_{-\infty}^{\infty} B(\mathbf{x}; \tau) g^*(\mathbf{x}; \tau - t) e^{-j2\pi f\tau} d\tau, \quad (2)$$

where $g(\mathbf{x}; t)$ is a Hamming window that divides $B(\mathbf{x}; t)$ into segments and performs windowing, and $*$ denotes the complex conjugate. The number of segments is $N = \text{len} - \text{sample} + 1$, where len is the length of $B(\mathbf{x}; t)$, and sample is the window width denoted by $\text{floor}(fs/resf)$, where $\text{floor}(x)$ rounds x to integer, fs denotes the video frame

Fig. 1 The interpretation of frequency variability (FV). We extract human breathing and tree motions at A and B respectively in a living-body video (a). The time-frequency spectrogram (c) and temporal peak frequencies (e) of human breathing present straight lines; while that (d) and (f) of background tree motions are not. The Poincaré plots are presented in (g) and (h) where FV values are estimated. (b) visualizes the negative exponential FV values that are high when meaningful subtle breathing motions appear.

rate, and $resf$ is the frequency resolution. Time frequency spectrograms of two representative subtle motions A and B extracted respectively at positions A and B in a living body video (Fig. 1 (a)), are illustrated in Fig. 1 (c) and (d).

We record the peak frequency FF_i^x of the local frequency spectrum in each time interval and obtain the temporal peak frequencies of $B(\mathbf{x}; t)$ as $(FF_1^x, \dots, FF_i^x, \dots, FF_N^x)$, $1 \leq i \leq N$. Waves of temporal peak frequencies of motion signals A and B are illustrated in Fig. 1 (e) and (f). From these plots, we can see that the wave corresponding to signal A (located in human chest region) is a constant line, while the wave corresponding to signal B (located in the background) are variable over time. These waves in turn indicate that there indeed is difference in the temporal variability of peak frequencies for meaningful human breathing and non-meaningful background tree motions.

In order to estimate the FV values of $B(\mathbf{x}; t)$ from temporal peak frequencies, we extend PPA to our work. PPA has been used in cardiovascular system to visually represent the HRV, which predicts the future cardiovascular risk in healthy individuals [14]. The Poincaré plot draws each point P_i denoted by (FF_i^x, FF_{i+1}^x) , resulting in a scatter diagram (see in Fig. 1 (g) and (h)). An ellipse is applied to fit this plot, and its SD indexes are given by

$$\begin{aligned} SD1(x) &= \sqrt{\text{VAR}\left(\frac{FF_i^x - FF_{i+1}^x}{\sqrt{2}}\right)}, \\ SD2(x) &= \sqrt{\text{VAR}\left(\frac{FF_i^x + FF_{i+1}^x}{\sqrt{2}}\right)}, \end{aligned} \quad (3)$$

where, VAR is a variance operator, $SD1$ and $SD2$ are the minor and major semi-axes of the fitting ellipse. From Eq. (3), we know that $SD2$ is equivalent to the standard deviation of points oriented along the line of identity (LI) that reflecting the level of long-term variability of peak frequency, while $SD1$ indicates the level of short-term variability of peak frequency. Therefore, by combining these two pieces of variability information, FV could be better estimated quantitatively through the computation of ellipse area as

$$FV(x) = \pi \cdot SD1(x) \cdot SD2(x). \quad (4)$$

Therefore, low FV values correspond to meaningful subtle changes, which have constant peak frequencies. A special case when the peak frequency is not in the target frequency band ($F_l \sim F_h$) is clearly illegal, even although the corresponding FV value is zero. We remove this case by adding a distance constraint to Eq. (4). Based on the Poincaré plot geometry, we found that the 1D target frequency band can be equivalently expressed by a 2D square (see the green square in Fig. 1 (g) and (h)). That means as long as point P_i locates in the green square, the corresponding peak frequencies are in the target frequency band. This finding can be mathematically represented through a distance equation among three points, P_i , P_{low} and P_{high} , by

$$L_1(P_i, P_{low}) + L_1(P_i, P_{high}) = L_1(P_{low}, P_{high}), \quad (5)$$

where L_1 is the Manhattan distance, $P_{low}(F_l, F_l)$ and $P_{high}(F_h, F_h)$ are vertices of the 2D square lying on LI.

Based on above observations, we conclude that under the distance constraint (Eq. (5)), low FV indicates that the corresponding $B(x; t)$ has an approximately stable peak frequency and can be regarded as a meaningful signal, while high FV indicates a signal with variable frequencies that to be regarded as non-meaningful ones. Thus, we considered that FV is a useful index to distinguish meaningful subtle changes and non-meaningful ones. To visualize our hypothesis, we show the FV values of subtle motion changes in a living-body video (a search and rescue use-case, Fig. 1 (b)). It shows that the FV values are low (i.e. the $\exp(-FV)$ values are high) when meaningful subtle breathing motions appear.

2.2 Frequency Variability Filter

On the basis of our knowledge of FV , we designed a frequency variability filter that passes only meaningful subtle color or motion changes with low FV values, and filters out non-meaningful background motions with high FV values.

First, we get FV values as follows. Given an input image signal $I(x; t)$, we obtain subtle changes $B(x; t)$ as done in [4]. We calculate the STFT of $B(x; t)$ by Eq. (2), and obtain

its temporal peak frequencies $(FF_1^x, \dots, FF_i^x, \dots, FF_N^x)$. Then we get the value $FV(x)$ of $B(x; t)$ by using Eqs. (3)–(5). After that, we design the frequency variability filter $FVF_\gamma(x)$ with a weight γ for adjusting the filter response as

$$FVF_\gamma(x) = (\text{Norm}(\exp(-FV(x))))^\gamma, \quad (6)$$

where $\text{Norm}(x)$ normalizes x value between 0 and 1. This filter has high values only when subtle changes having low frequency variability and within the target frequency band appear, which means that it can pass only meaningful subtle changes and ignores non-meaningful ones.

2.3 Video Magnification under Background Motions

We applied the proposed frequency variability filter to the linear Eulerian video magnification method (Linear EVM) [4] for color magnification. Linear EVM uses Gaussian pyramid to decompose input signal $I(x; t)$ to $I^l(x; t)$, where l denotes the pyramid level, and selects the target frequency components desired to be magnified from intensity changes $B^l(x; t)$ by using a temporal bandpass filter $BPF(t)$.

However, $BPF(t)$ only is not enough to guarantee the selected frequency components absolutely extracted from meaningful subtle changes, due to that non-meaningful ones also have these components. To detect only meaningful subtle color changes, we design a frequency variability filter $FVF_\gamma^l(x)$ from $B^l(x; t)$ through Eqs. (3)–(6). By combining $FVF_\gamma^l(x)$ and $BPF(t)$, the signal within the target frequency band of meaningful subtle changes can be expressed by

$$B_{FVF}^l(x; t) = BPF(t) \otimes (FVF_\gamma^l(x) \circ B^l(x; t)), \quad (7)$$

where $\circ$ is an element-wise product. After this process, we multiply $B_{FVF}^l(x; t)$ by a factor α and obtain the color magnification signals $\hat{I}^l(x; t)$ at pyramid level l as

$$\hat{I}^l(x; t) = I^l(x; t) + \alpha B_{FVF}^l(x; t). \quad (8)$$

Through this process, we obtain good color magnification results under the presence of background motions.

On the other hand, we applied the proposed frequency variability filter to the phase-based method (PVM) [5] for motion magnification. PVM focuses on using local phase variations rather than intensity changes to represent local motions. To obtain local phase, complex steerable pyramid [15], which contains a set of filters $\psi_{\omega, \theta}^l$ at different spatial scale ω , orientation θ , and level l , is applied to decompose $I(x; t)$ into different spatial frequency bands as

$$S_{\omega, \theta}^l(x; t) = \psi_{\omega, \theta}^l \otimes I(x; t) = A_{\omega, \theta}^l(x; t) e^{i\phi_{\omega, \theta}^l(x; t)}, \quad (9)$$

where $A_{\omega, \theta}^l(x; t)$ is amplitude and $\phi_{\omega, \theta}^l(x; t)$ is phase. After this process, PVM obtained subtle phase changes $C_{\omega, \theta}^l(x; t)$ on which users applied a bandpass filter $BPF(t)$ to extract target components that to be magnified. For details, see [5].

However, $BPF(t)$ also extracted components from non-meaningful signals, resulting in artifacts or blur in magnified videos. To cut them off and detect only meaningful

ones, we design the phase-based frequency variability filter $FVF_{\omega,\theta}^{l,\gamma}(\mathbf{x})$ from $C_{\omega,\theta}^l(\mathbf{x}; t)$ as follows.

We consider a phase signal $C_{\omega,\theta}^l(\mathbf{x}; t)$ at position $\mathbf{x}$ and time t , and use Eq. (2) to obtain its temporal peak frequencies. Then we design the filter $FVF_{\omega,\theta}^{l,\gamma}(\mathbf{x})$ by using Eqs. (3)–(6), and obtain the signal desired to be amplified as

$$\tilde{C}_{\omega,\theta}^l(\mathbf{x}; t) = BPF(t) \otimes (FVF_{\omega,\theta}^{l,\gamma}(\mathbf{x}) \circ C_{\omega,\theta}^l(\mathbf{x}; t)). \quad (10)$$

Finally, we obtain the synthesis phase where meaningful subtle phase changes are only magnified as

$$\hat{\phi}_{\omega,\theta}^l(\mathbf{x}; t) = \phi_{\omega,\theta}^l(\mathbf{x}; t) + \alpha \tilde{C}_{\omega,\theta}^l(\mathbf{x}; t). \quad (11)$$

Similar to [11], [12], phase unwrapping is used to correct the unstable phase jumps due to the periodicity of the phase between $[-\pi, \pi]$.

3. Experiments

To validate the effectiveness of the proposed method, we conducted experiments on real videos and synthetic ones with ground truth available. We evaluated the performance qualitatively for real videos and quantitatively against ground truth for synthetic ones. The parameters for each experiment are listed in Table 1. We process these videos in YIQ color space, and the source and magnified videos can be found at: <https://github.com/xxdragon163/VMCBM/tree/master>.

3.1 Real Videos

We compared our color magnification technique with two state-of-the-art methods, Linear EVM [4] and acceleration [11], which can perform color amplification without user interventions in the same way as our method does.

As a first experiment, we show that our method can amplify subtle face color changes when there is no background motions (e.g. eye blinking). Figure 2 shows a face video [4] where the face color changes as the blood flows through the face of a stationary man. Results show that our method is able to amplify the meaningful subtle face color changes as well as Linear EVM [4] does. However, acceleration method [11] seems to produce different color magnification. For example, its fringe patterns in the spatio-temporal slice seem to be different from that of Linear EVM and ours. This may be due to that the accelerations of face color changes are amplified rather than color changes themselves.

Table 1 Parameters for all videos.

Video	γ	α	f	fs	$F_l - F_h$	$resf$
living-body	40	20	0.3	50	0.25-0.37	0.1
face [4]	30	100	0.92	30	0.83-1	0.15
face2	30	50	1.5	50	0-2	0.1
vibration	20	18	10.6	50	9.5-11.5	0.1
drum [7]	10	11	30	1900	28-32	6
Sim1	30	0-70	6	30	5-7	0.2
Sim2	30	10	0.5	30	0.4-0.6	0.2

On the other hand, we assess the performance of our method on magnifying face color changes when non-meaningful eye blinking exists. Figure 3 shows various magnification results of the face2 video. In the original video, face color changes are hardly noticeable with no magnification (see the slice in Fig. 3 original-top). Processing this video with Linear EVM succeeds in magnifying the subtle color changes on the face, but creates artifacts around eyes (see in Fig. 3 Linear EVM-bottom). This is because Linear EVM cannot remove eye blinking motions, but magnifies them along with face color changes. Acceleration method seems not amplify the color changes but their accelerations, and produces artifacts around eyes due to that the accelerations of eyes blinking motions are amplified. In contrast, based on the designed frequency variability filter, our method can correctly magnify only meaningful face color changes, without artifacts around eyes. These results also demonstrated that our method may have potential application in biomedical field for monitoring human heart rate.

Next, we compared our motion magnification technique with three state-of-the-art methods, PVM [5], DVMAG [8] and acceleration method [11]. These methods can amplify subtle motion changes in the video. Figure 4 shows a mechanical use-case for visualizing the mechanical vibration. In this case, a vibration generator induces subtle mechanical vibrations on a white object while plants swing in background. Our goal is to clearly reveal the mechanical vibrations by magnifying only the object vibrations and ignoring the plant movements. PVM can significantly amplify the mechanical vibrations, but creates additional artifacts due to the background plant movements. DVMAG method requires manual segmentation to select a ROI (indicated in yellow) where the object vibrations are magnified. However, transitional zones between ROI and background need to be corrected by image inpainting, and moreover, plant motions in ROI are also amplified thus resulting in artifacts. Acceleration method also induces artifacts and blur due to that the accelerations of plant movements are magnified. In contrast, by using the frequency variability filter our method

Fig. 2 Face color magnification of a stationary man without eye blinking.

Fig. 3 Face color magnification of a stationary man with eye blinking.

Fig. 4 Magnification results of mechanical vibrations of the white object, with background plant movements.

Fig. 5 Magnification results of drum with drumstick motions.

can magnify only mechanical vibrations of the white object without artifacts caused by background plant movements, and without manual interventions.

Additionally, Fig. 5 shows a case for drum beating video [7] in which a drumstick moves in background. Our proposed motion magnification method automatically ignores the drumstick movements and can magnify the subtle vibration of the drum without user interventions.

3.2 Controlled Experiments

In this part we quantitatively assess the performance of our method with structural similarity (SSIM) between each magnified synthetic video and ground truth. SSIM = 1 denotes exact ground truth similarity and 0 denotes no similarity.

To assess the ability of magnifying the meaningful vibration of a target object under the presence of background motions, we conducted experiments on a 10-second synthetic video, **Sim1** (see Fig. 6, top-left). The ball named Tball in **Sim1** is a target object to be magnified, while other two balls (Bball1 and Bball2) are background objects that need to be ignored. Tball has vertical ball motions defined as $d_{Tball} = 0.25 \cdot \sin(2\pi \frac{f}{f_s} j)$, where $f = 6$ Hz, $f_s = 30$ fps, and j is the frame number. In addition, Bball1 also has vertical subtle motions defined as $d_{Bball1} = 0.5 \cdot \sin(2\pi \frac{f_{Bball1}}{f_s} j)$, where f_{Bball1} varies from 2 to 9 Hz with increments of 0.5 Hz for every 20 frames. Bball2 has vertical motions same to Tball, but its amplitude is 0.5; moreover, Bball2 has horizontal slow large motions on the screen from left to right

Fig. 6 Various magnification results of Sim1 against the ground truth.

Fig. 7 Left: SSIM with ground-truth for each frame of Sim1. Right: mean SSIM with the ground truth over different amplification factors.

with a speed of 0.25 pixel/frame. To obtain the ground-truth of meaningful motion magnification, we created magnification videos by changing d_{Tball} to $\alpha \cdot d_{Tball}$.

Figure 6 shows various magnification results of **Sim1**. PVM [5] method produces background artifacts due to that it cannot ignore the background motions of Bball1 and Bball2. DVMAG [8] can amplify the ROI indicated in yellow, but also amplified the background motions of Bball1 and Bball2 which are in or partly in the ROI. Acceleration method [11] magnifies the accelerations of subtle vibrations of both target and background balls, resulting in artifacts in background. Our method, however, generates a motion magnification that closely resemble the ground truth, without artifacts caused by Bball1 and Bball2. Figure 7 (left) shows the SSIM for each magnified frame against the ground truth ($\alpha = 6$). It shows that our method achieves higher SSIM than compared methods owing to the designed frequency variability filter for handling background motions. Figure 7 (right) shows how our method behaves with different amplifications α (from 0 to 70). Here we estimated the mean SSIM of all magnified frames at each α against ground truth. It shows that our method can handle larger amplifications with less errors and has the slowest rate of degradation over other techniques.

To explore how background motions degrade the magnification result and how such degradation is handled by our method, we examined the synthetic video **Sim2** (see Fig. 8 top-left). **Sim2** was created by adding the background motions of Bball1 and Bball2 to a baby video [4]. Our goal is to magnify the breathing motions of the baby while ignore the

Fig. 8 Various magnification results of Sim2 against the ground truth. Top-left: SSIM for each magnified frame against the ground truth.

motions of Bball1 and Bball2. To obtain the ground truth magnification of **Sim2**, we use PVM [5] to magnify only the baby video in the range of 0.4 to 0.6 Hz ($\alpha = 10$), while keeping background motions unchanged. Figure 8 shows the magnification results for **Sim2**. Though PVM and DVMAG [8] achieve good performance on magnifying the breathing motions, they incur artifacts in background due to the motions of Bball1 and Bball2; and moreover, DVMAG causes a transitional zone between the magnified and non-magnified region that needs to be manually corrected. Acceleration method [11] seems not to amplify the real breathing, for example its slice of the red line on baby chest is different against the ground truth; and it also produces artifacts due to the magnification of accelerations of background motions. In contrast our method, using the frequency variability filter, can amplify only the breathing motions that resemble the ground truth, without negative effects of Bball1 and Bball2. Figure 8 (top-right) shows the SSIM for each magnified frame against the ground truth. PVM and acceleration methods get low SSIM in almost all frames due to the background motions. DVMAG magnifies the breathing motions in ROI, but produces artifacts during the time background motions appear in ROI. Our method can best handle the background motions while amplifying subtle breathing motions that resemble the ground truth in all frames.

4. Conclusions

We proposed a new method for magnifying only meaningful subtle color and motion changes under the presence of background motions, without manual interventions that previous methods required [8]–[10].

We found that the peak frequency of meaningful subtle changes keeps constant over time, while that of non-meaningful ones caused by background motions varies during time intervals. Therefore, we use the temporal variabil-

ity of peak frequency (i.e. frequency variability) to design a frequency variability filter that passes only meaningful subtle changes and ignores non-meaningful ones. This filter enables us to produce more impressive magnification results without artifacts or blur than those of state-of-the-art methods. Results also demonstrate that our method can expand the application scope of video magnification for visualizing a meaningful and fascinating small world, and show potentials to detect vital signs (such as heart rate and respiratory rate) in biomedical field and search and rescue missions, and to measure vibrations in mechanical engineering.

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