

An Efficient Eulerian Video Magnification Technique for Micro-biology Applications

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Abstract. *The micro-biology videos often contain motions of particles which are not visible to naked eye. Therefore an efficient motion magnification technique is required to magnify these motions. A time efficient Eulerian video magnification technique for micro-biological applications is proposed. The proposed technique utilizes the concept of time and spatial uniformity to reduce the computational complexity. Simulation results reveal that the proposed scheme is almost four times efficient and more accurate as compared to state of art video magnification technique.*

Keywords

Eulerian video magnification, micro-biological applications, spatial-temporal processing

1. Introduction

Micro-biology videos contain small moving micro-organisms which are often not visible to naked eye. As micro-organisms (such as bacteria), can be harmful to human beings, there is a need for a technique capable of detecting and magnifying small motions of these micro-organisms. The enhancement of these minute motions (hidden information) is helpful for different applications (including density estimation and behavior analysis) [1], [3–6], [12]. Traditionally, microscope is an essential tool in micro-biology to visualize micro-organisms. However, the reliability of microscopic analysis of images is dependant on equipment used for visualization [10]. In literature [7], [14–16], visual motion magnification techniques have been proposed to highlight invisible changes in videos.

As visual motions occur at different amplitudes in spatial and temporal frequencies, it is difficult to observe small movements of micro-organisms. Previously attempts have been made to reveal subtle motions in videos [7], [14], [15]. Liu et al. [7] proposed a motion magnification technique to magnify small motions in videos, by enhancing specific cluster of pixels. The technique enhances small motions

only in the specified area. In [15], use of Langrangian motion estimation [2] to enhance mechanical motions in cartoon animation is presented. The technique [15] is not only computationally expensive but also produce significant amount of errors in motion estimation [16]. Since Eulerian motion estimation technique [2] does not involve costly optical flow computation and is less sensitive to noise, Wu et al. [16] proposed to use it for video magnification to observe the motion of visual changes at specific location as they flow through time. Although Eulerian video magnification technique [16] provides robustness, however the quality of magnification is dependant on magnification factor. In high spatial frequencies, as magnification factor is increased, it introduces unwanted/noise artifacts. To reduce these unwanted noise produced by the magnification factor, steerable pyramids [11] and complex steerable pyramids using fourier decomposition are proposed [13]. These techniques result in over-complete pyramid decomposition and are computationally expensive [14]. The increased computational cost and over completeness of steerable pyramids make current phase based motion magnification inefficient.

Wavelet pyramid decomposition allows interpretation of information at different resolutions (coarse-to-fine). It analyzes the image at coarse resolution and then gradually increases image resolution [8]. As wavelet decomposition utilizes information gathered from both coarse and fine scales for magnification, the final magnified video is reconstructed with high precision. In this paper, use of wavelet representation for pyramid decomposition in Eulerian video magnification technique is proposed. The proposed technique decomposes the video frames into spatial bands using wavelet decomposition and analyze the information content at different scales. To magnify the desired frequencies, temporal processing is performed on each spatial band. The proposed technique not only magnifies the insignificant minute visual changes but also avoids spatial aliasing and is noise free. To demonstrate the effectiveness of proposed technique, quantitative comparisons on four microbiological videos have been provided. The results demonstrate that the proposed technique is almost four times efficient and provides magnification without introducing unwanted artifacts.

2. Proposed Technique

Let $P_t^\beta(\bar{u})$ be the intensity of color input video at location $\bar{u} = [u_1 \ u_2]$ and at time t , where β represents red, green and blue color bands i.e. $\beta \in \{R, G, B\}$. The gray scale image $P_t(\bar{u})$ is

$$P_t(\bar{u}) = 0.2989 \times P_t^R(\bar{u}) + 0.5870 \times P_t^G(\bar{u}) + 0.1140 \times P_t^B(\bar{u}). \quad (1)$$

To reduce the computational complexity, the P_t is spatially down-sampled using Bicubic interpolation with a factor η i.e.

$$\tilde{P}_t(\bar{u}_\eta) = P_t(\bar{u}) \downarrow \eta \quad (2)$$

where value of $\eta \in [0, 1]$.

The existing Eulerian magnification [16] decomposes the image into different levels using Laplacian and Gaussian pyramids. However, there are two major limitations i.e. over-completeness (by factor of 4/3 and 2 in one and two dimensions respectively) and non-utilization of information present in high pass images. To overcome this limitation, the proposed technique uses Discrete Wavelet Transform (DWT) based on Quadrature Mirror Filters (QMF). QMF filters are suitable for multi-resolution decomposition and pyramid coding. Orthonormal QMF filters provide perfect reconstruction without error introduction [9]. Different components of DWT are

$$\{\tilde{P}_t^A, \tilde{P}_t^H, \tilde{P}_t^V, \tilde{P}_t^D\} \xleftarrow[(\text{level } 1)]{\text{DWT}} (\tilde{P}_t) \quad (3)$$

where A, H, V, D represent approximation, horizontal, vertical and diagonal detail components respectively.

To extract frequency bands of interest, temporal processing is performed i.e. each subband is interpolated with a temporal band pass filter. The temporal processing not only attenuates signals out of interest band but also smooths the resulting signal. For example, if the aim is to find out pulse rate then frequencies within 0.4-4Hz might be selected. The choice of filter depends on type of application. In proposed technique, Infinite Impulse Response (IIR) filter is used as it amplifies both colour and motion. To compute the filtered subband $F_t^k(\bar{u}_\eta)$, we use recursive difference (4) where wavelet spatial band $\tilde{P}_t^k(\bar{u}_\eta)$ is taken as present input signal and $F_{t-1}^k(\bar{u}_\eta)$ as past filtered output in time domain.

$$F_t^k = \sum_{i=0}^M b_i \tilde{P}_{t-i}^k - \sum_{j=0}^N a_j F_{t-j}^k \quad (4)$$

where $b_i, i = 0, 1, 2, \dots, M$ and $a_j, j = 0, 1, 2, \dots, N$ are the coefficients and k represents different temporal components of F_t .

The resultant magnified output signal I_t^k is given by

$$I_t^k = \gamma \times F_t^k \quad (5)$$

where γ is magnification factor. γ can be computed using first-order Taylor series expansion [16] or can be specified by the user. Taylor series approximations works well for

small magnification value. But for larger magnification, it produces inaccurate results and introduces noisy artifacts. If displacement function $\delta(t)$ due to observed motion at time t in an image does not lie within the range of temporal filter passband, it is attenuated by a certain factor and modified magnification factor γ_m is obtained (6) which supports large magnification for observed motion $\delta(t)$ in high spatial frequencies.

$$\gamma_m = \delta(t) - \lambda/8 \quad (6)$$

where cut-off spatial wavelength λ for moving signals is taken as $2\pi/\omega$ and ω is the spatial frequency (determined by Fourier transform).

To obtain processed output signal G_t , wavelet pyramid is reconstructed by upsampling using bicubic interpolation, filtering and summing the individual sub-bands i.e. I_t^A, I_t^H, I_t^V and I_t^D

$$(G_t) \xleftarrow[(\text{level } 1)]{\text{IDWT}} \{I_t^A, I_t^H, I_t^V, I_t^D\}. \quad (7)$$

Let V_t be the result of upsampling the processed frame by factor η (to regain the original video resolution, while preserving the vital structural information)

$$V_t(\bar{u}) = G_t(\bar{u}_\eta) \uparrow \eta. \quad (8)$$

To regenerate a coloured output frame having red, green and blue coloured bands with the magnified motion, the processed magnified signal $V_t(\bar{u})$ is added back into the original signal $P_t^\beta(\bar{u})$

$$\hat{P}_t^\beta(\bar{u}) = P_t^\beta(\bar{u}) + V_t(\bar{u}) \quad (9)$$

where $\hat{P}_t^\beta(\bar{u})$ is coloured frame at location \bar{u} and at time t .

To enhance the efficiency, above mentioned steps are performed on every alternate frame of video. The output (magnified) video highlights the hidden details which are not visible to the naked eye.

3. Simulation Results

Wu et al. [16] and proposed technique are evaluated on various microbiological videos. The parameters used for videos are listed in Tab. 1. For all videos, IIR filter with passband of 0.4 Hz (Γ_1) to 0.005 Hz (Γ_2) and spatial wavelength (λ) 16 are used. Accordingly, magnification factor (Ω) 30 and 100 are chosen to achieve desired magnification in output video. Table 2 lists the quantitative comparisons

Videos	Ω	λ	Γ_1 (Hz)	Γ_2 (Hz)
Infusoria	30	16	0.4	0.05
Motile	30	16	0.4	0.05
Physarum	100	16	0.4	0.05
Water	100	16	0.4	0.05

Tab. 1. Parameters for Eulerian magnification.

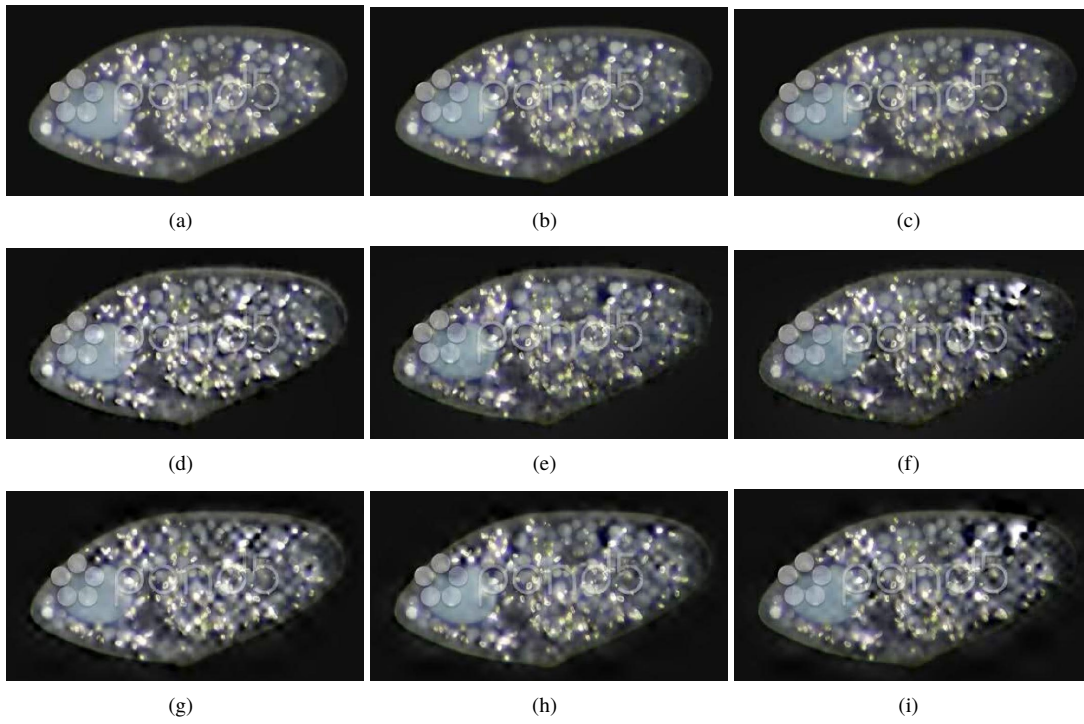


Fig. 1. Infusoria: (a–c) original frames, (d–f) Wu et al. [16], (g–i) proposed technique.

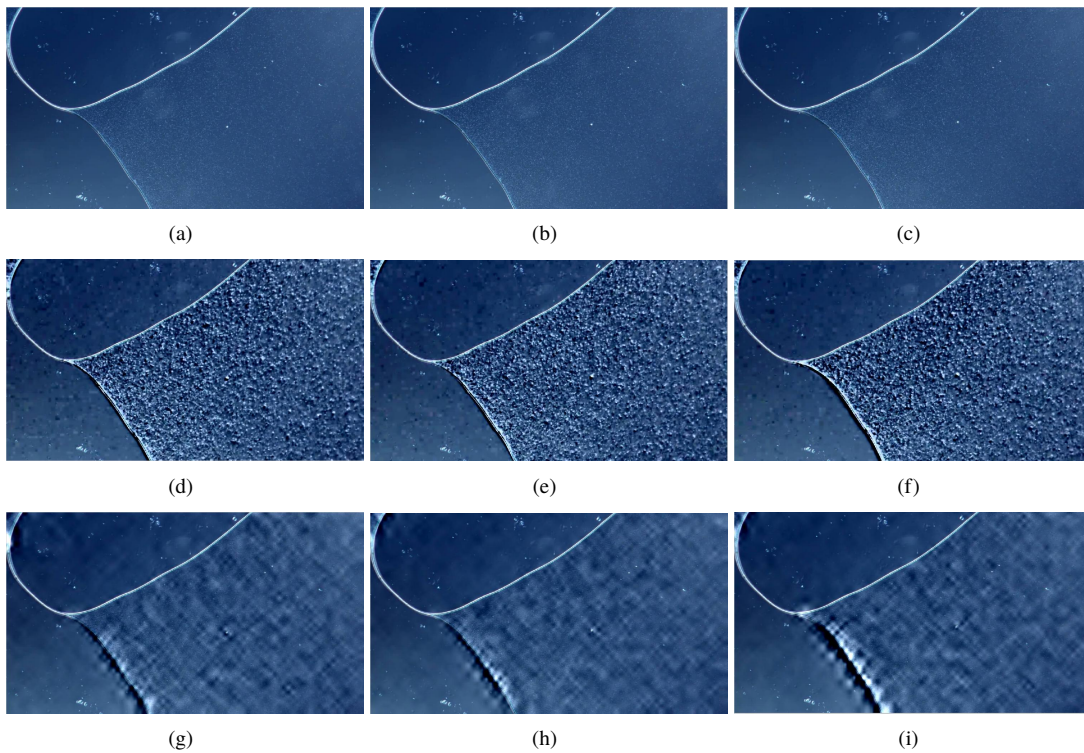


Fig. 2. Motile bacteria: (a–c) original frames, (d–f) Wu et al. [16], (g–i) proposed technique.

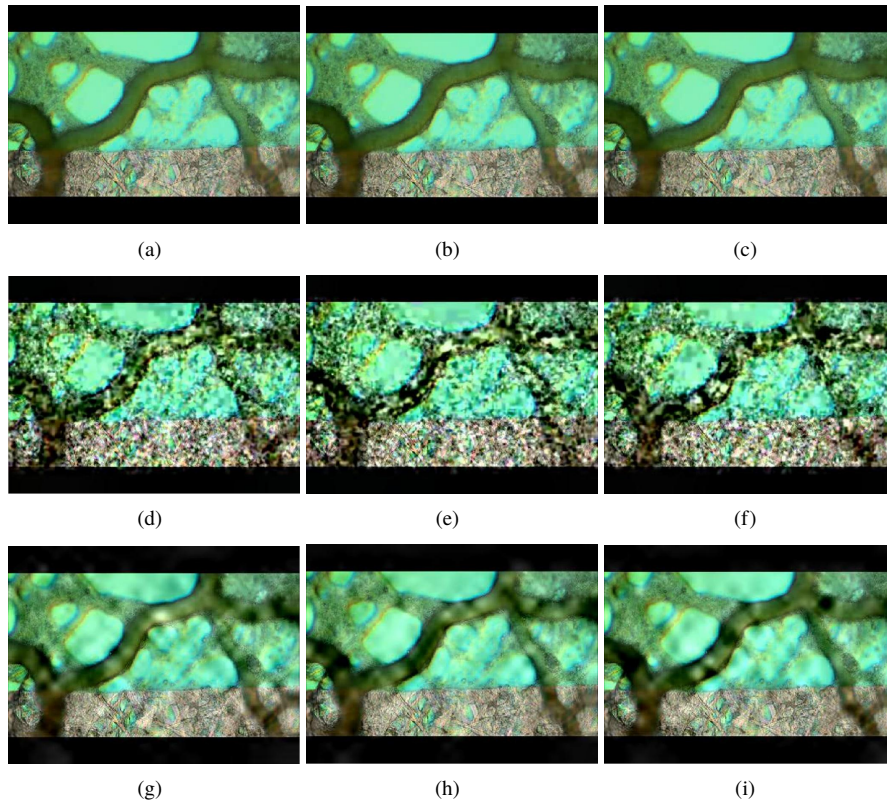


Fig. 3. Physarum: (a–c) original frames, (d–f) Wu et al. [16], (g–i) proposed technique.

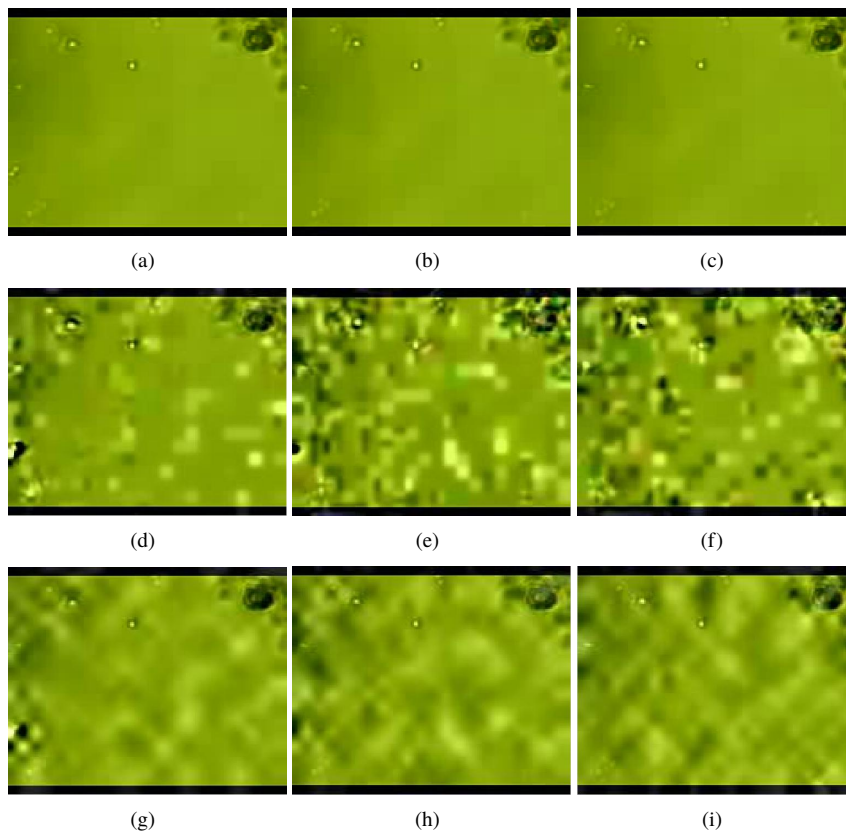


Fig. 4. Water: (a–c) original frames, (d–f) Wu et al. [16], (g–i) proposed technique.

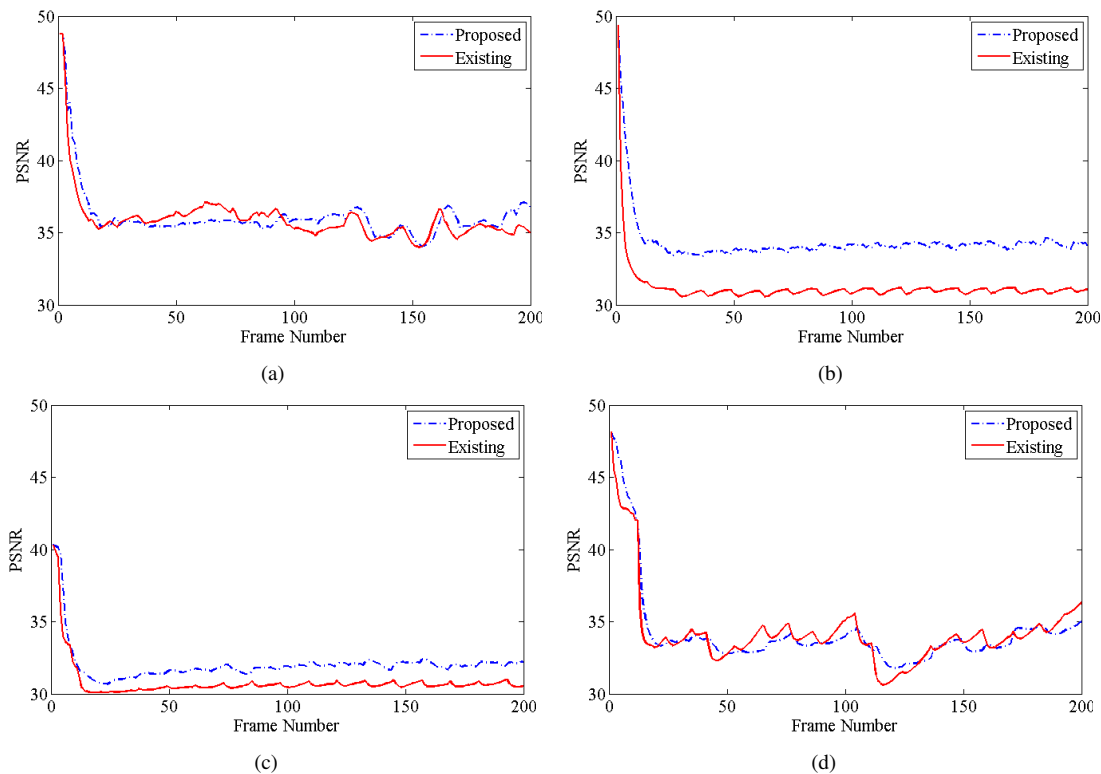


Fig. 5. PSNR plots: (a) infusoria, (b) motile, (c) physarum, (d) water.

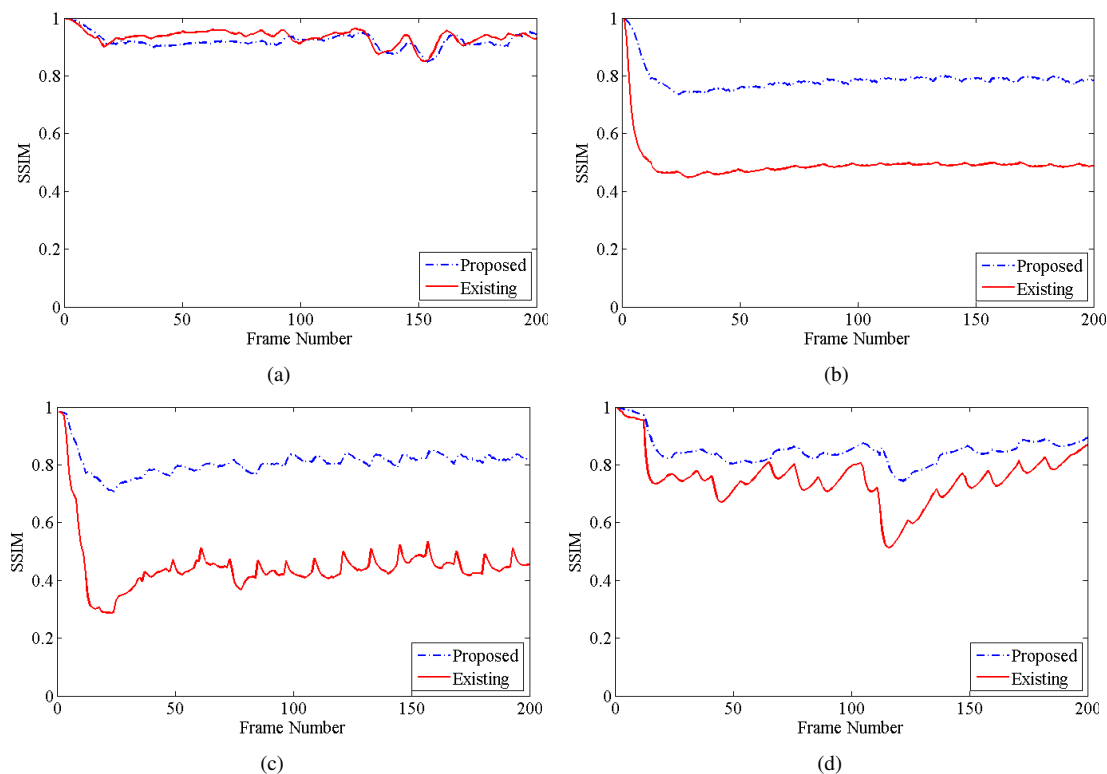


Fig. 6. SSIM plots: (a) infusoria, (b) motile, (c) physarum, (d) water.

Videos	PSNR (dB)		SSIM	
	Wu et al. [16]	Proposed	Wu et al. [16]	Proposed
Infusoria	35.6493	36.0433	0.9362	0.9242
Motile	30.9901	33.9569	0.4900	0.7788
Physarum	30.6622	31.8964	0.4491	0.8081
Water	33.5203	33.4387	0.7360	0.8410

Tab. 2. Average quantitative measures.

Video	Frame Rate	Total Frames	Resolution	Processing Time (s)		Reduction Factor
				Wu et al. [16]	Proposed	
Infusoria	30	325	272×480	336.207	63.9619	5.25
Motile	30	393	720×1280	2258.98	407.353	5.54
Physarum	30	251	300×400	200.112	68.0576	2.94
Water	24	324	144×176	122.405	34.2163	3.57

Tab. 3. Computational complexity results.

performed using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [17] to evaluate and compare the quality of videos magnified using proposed technique with the state of the art technique [16].

Figure 1(a–c) shows the frames of micro-organism Infusoria input video when the water pumps out of the cell by contraction. Water and food particles move inside and outside of oral groove, which causes contraction in cilia (outer layer) and contractile vacuole. This movement is not visible to the naked eye but can be made visible after applying Wu et al. [16] and proposed Eulerian magnification technique (Fig. 1(d–i)). However, the results of Wu et al. [16] introduces unnecessary artifacts in the magnified video whereas the proposed technique preserves the smoothness of video by removing noise and unwanted artifacts.

Figure 2(a–c) shows the original frames of Motile bacteria motion video. The smooth gliding of bacterial leaving a black copious slimy trail behind is not clearly visible and they appear almost static. However, using existing Wu et al. [16] technique, the motion of bacteria is magnified along with noise (see Fig. 2(d–f)). Whereas the proposed technique, amplifies the motion and increases the visibility to differentiate motion of bacteria (Fig. 2(g–i)).

Figure 3(a–c) shows the original frames of Physarum Polycephalum streaming video. Physarum Polycephalum lives in isolation in slime moulds. Its streaming is dependant on to and fro (nearly invisible) movement of plasmodium. The contraction and relaxation of cell membrane forces plasmodium to move back and forth within periphery of cell. After applying [16] (Fig. 3(d–f)), noise is also amplified along with movement. However, the proposed technique only amplifies movement of plasmodium in moulds and suppresses the noise to minimum level (Fig. 3(g–i)).

Potable drinking water video frames are shown in Fig. 4(a–c). Note that the bacteria present in water are not identifiable (as the video is nearly still). Figure 4(d–f) shows that unwanted noise artifacts are introduced after applying Eulerian video magnification technique [16]. However the

proposed technique not only identifies moving bacteria (black artifacts) in drinking water (which are harmful) but also de-noises the video and produces smooth results (Fig. 4(g–i)).

Figure 5 shows the PSNR plots of exiting Wu et al. [16] and proposed techniques. It can be seen that the results of Wu et al. [16] and proposed techniques are comparable for infusoria and potable drinking water videos (Fig. 5(a, d)). For Motile bacteria and Physarum videos (Fig. 5(b, c)) the proposed technique provides much better results as compared to Wu et al. technique [16]. The average PSNR linked to Fig. 5 is given in Tab. 2. Figure 6 shows the SSIM plots of Wu et al. [16] and proposed techniques. It can easily be concluded from the results that proposed technique yield mostly better SSIM values as compared to existing Wu et al. [16] technique. The average SSIM linked to Fig. 6 is given in Tab. 2.

In Tab. 3, computational complexity results of MATLAB implementations of Wu et al. [16] and proposed techniques. The proposed technique yields almost 4 times faster results than the Wu et al. [16] while preserving the smoothness of the videos.

4. Conclusion

A time efficient Eulerian video magnification technique for micro-biological applications is proposed. The technique is four times efficient as compared to existing technique. The technique utilizes the concept of time and spatial uniformity to reduce the computational complexity. Visual and quantitative analysis verifies the effectiveness of the proposed technique as compared to state of art video magnification technique.

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