Video Magnification Techniques: Medical Applications and Comparison of Methods

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Abstract. The unassisted visual system cannot note minute temporal variations in video and image sequences. In many applications, these differences and small signals are highly informative. A new technique used to expose video variations by measuring and amplifying video variations over time in a fixed position (pixel) was used to Eulerian video magnification (EVM). The objective of the study is to investigate and evaluate different processes for the creation and testing of EVM techniques and video quality parameters for each one of those methods. This research employed four new methods; EVM, Riesz pyramid for fast phase-based video magnification (FPBM), phase-based video magnification (PBM), and Enhanced Eulerian video magnification (E2VM). The experimental findings compared with their output for certain enlargement methods; time and quality parameters of image. A new magnification method is required based on the study of the exiting methods, which takes account of noise elimination, video quality and time reduction.

Keywords: Eulerian video magnification, phase-based video magnification, fast phase-based video magnification, Enhanced Eulerian video magnification.

1. Introduction
There are some small differences in a video that are difficult to discern by the human eye because the spatial perception is reduced. In many applications, particularly for biomedical applications, these differences may contain useful information for measuring physiological signs and indicators in patterns. Blood flow through the circulatory system, for example, induces irreversible shifts through skin tone that are very useful for heart activities [1-11]. Often, as the carotid artery induces slight oscillations in the human head as blood circulates from the heart to the mind in the human body. This oscillation used to assess heart rate, although it is difficult to see from the human eye [12-15]. Similarly, arterial blood pressure in many locations (e.g wrist, arm, neck and leg), while difficult or impossible for people to see, can be magnified based on analysis of video sequence to measure cardiac activity [16-18]. Another example, motion due to the inhalation process may be of low spatial capability in the video making it difficult for the human eye to detect. This motion can also be magnified and extracted from the video sequence to reveal respiratory activity [19-24].
Other examples for using video magnification techniques in such medical applications, including, SpO2 extraction [25], heart failure monitoring [26], surgery [27-29], laparoscopy [30, 31], detection of limb ischemia [32], examining in vivo tympanic membrane mobility [33], intraoperative assessment of vascular function [34], free flap monitoring [35], retinal angiography [36] and stress detection, anxiety and depression by visual micro motions [37]. In addition, the video magnification techniques may show promise for applications in veterinary, animal welfare and zoological applications [38-42].

The importance of these interesting activities motivates the use and develop new video magnification techniques. Liu et al. [43] first suggested video magnification technique to magnify subtle motions in a video sequence and detect interesting mechanical behaviour based on Lagrangian perspective and optical flow calculations. Limitations in [43] include complexity and long execution time make it impractical for industrial and biomedical applications. Wu et al. [44] later suggested Eulerian Video Magnification (EVM) to see the video sequence's subtle temporal variations invisible to the human eye. EVM is based-Eulerian view where fluid, velocity and pressure properties of voxel develop over time. Though EVM manages to improve temporal movements and colour changes in videos and removes expensive optical flow calculation [43], it supports only minor enlargements at large spatial frequencies, linearly increasing the noise level by a greater magnification factor. Often, certain unwanted movements may increase during the amplification of the skin colour. Wadhwa et al. [45] Suggested a modern Eulerian protocol based on complex steerable pyramids and a phase based-optical flow approach to resolve those problems. Their system supported greater enlargements and less noise than the EVM has fewer artifacts and less noise. Their suggested technique can also be used in the case of colour amplification to mitigate and eliminate low amplitude motions. However, constructing, completing and running is more complicated, costly and long than EVM. Moreover, expanded videos may be incoherent depending on their process when certain frame sequences have a noisy signal period. Through a new, compact picture pyramid, the Riesz pyramid, they expanded their work to reduce overall execution time, create cost and movements, instead of a complex steerable pyramid [46]. The major restrictions of their work are that the Riesz pyramid struggles to retain the influence of an input signal that could trigger minor errors. Some of the drawbacks of EVM remain to the system [44]. Another study [47] suggested for an EVM enhanced (E2VM) post-processing technique. To increase motion without noise amplification E2VM relies on EVM as spatio-temporal motion analysis devices and picture warping between videos and magnified ones. E2VM also supports greater enlargement and substantially less affected by frame noise, as pixel values are not changed. This is time-consuming though and during image warping some amplification requirements may be missed. Furthermore, EVM defects limit E2VM results. Al-naji et al. [48] a framework built for solving such problems as time and sound rises and decreased video quality has been suggested, in recent research. The system proposed based-wavelet decomposition, the filter and image denoising in the Chebyshev bandpass, and may increase movement from source images. The device has achieved previous methods for minimising noise and processing time.

This review paper, therefore, provides researchers with more opportunities to recognise the limitations of the current wide-up approaches and can open the way to the alternative wider video approach, which is the key consideration of noise removal, video quality and time reduction. The contributions of this study are as follows.

1. Analyse, compare, and summarise most common video amplification (i.e. EVM, PBM, FPBM and E2VM) for internal structure, performance and limitations.
2. Compared to video source quality based on 10 parameters of video quality [49-58] are utilised to measure which groipng method offers better techniques.
3. Measured efficiency, quality and execution time for all techniques.

The rest of the paper organised as follows. Video magnification methods given in section 2. The objective video quality parameters presented in section 3. Section 4 explains the experimental results & discussion. Finally, conclusions are presented in section 5, which also highlights some future recommendations.
2. Video Magnification Methods

2.1. Eulerian Video Magnification (EVM)

EVM is the video processing process which magnifies the video and picture sequence with time also reveals subtle temporal changes motion and colour variations that make it visible to the eye of the human person. The spatial-time phase in EVM in which subtle variations in a source video observed. Every frame of the picture sequence is broken down by an analytical process, the Laplacian pyramid, in many different layers in frequency and resolution. Then, the processing of time filters by the application of a bandpass filter (B.P.F.) at certain frequencies corresponding to an operation carried out on each spatial unit. These bands then amplified by the amplification factor (M), which can be described by the consumer. In order to produce an amplified video, amplified signals attached to regular input signals and collapsed. Let \( I(x, t) \) demonstrate the strength of an image at location \( X \) at time \( t \), to explain the relationship between motion enlargement and time processing and how the magnification mechanism works. The sensitivity of the image function after translation:

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

If the motion function is an initial motionless an image function, then the movement function \( \delta(t) \) and the motion function \( I(x, 0) = f(x) \). The picture strength function can be calculated on a track, according to the Taylor series expansion of one dimension [59] as

\[
I(x, t) = f(x) + \delta(t) \frac{\partial f(x)}{\partial x} \tag{1}
\]

The expansion of the Taylor series can take place on a double-dimensional image. We assume that intensity \( B(x, t) \) is the product of applying \( I(x, t) \) to a temporal method of filtering. \( B(x, t) \) can be expressed with a motion \( \delta(t) \) falling in a passband filter according to the relationship.

\[
B(x, t) = \delta(t) \frac{\partial f(x)}{\partial x} \tag{2}
\]

To get a magnified intensity function of the following: \( I_m(x, t) \), \( I(x, t) \). The magnification factor \( M \) will multiply by \( B(x, t) \).

\[
I_m(x, t) \approx I(x, t) + M B(x, t) \tag{3}
\]

In \( I_m(x, t) \) magnified intense-function equations (2–4) depending on the relation:

\[
I_m(x, t) = f(x) + (1 + M) \delta(t) \frac{\partial f(x)}{\partial x} \tag{4}
\]

Finally, a link between temporary band-passing and magnified motion is formed with the first order Taylor-expansion holds for amplification larger passing \( (1 + M) \)

\[
I_m(x, t) = f(x + (1 + M) \delta(t)) \tag{5}
\]

From Eq it's obvious, (6) the \( \delta(t) \) spatial motion function of the first f(x) of the imagery, amplified by \( (1 + M) \) factor.

For completeness, we assume now that the \( \delta(t) \) movement signal has not been fully indexed by the temporal filter passband and is indexed by \( k \) to \( \delta_k(t) \), where \( k \) is an element of different spectral time components of \( \delta(t) \). The temporal filtering of each \( \delta_k(t) \) by the value of \( \gamma_k \) to get a new bandpass signal \( B(x, t) \) attenuated as:

\[
B(x, t) = \sum_k \gamma_k \delta_k(t) \frac{\partial f(x)}{\partial x} \tag{6}
\]

The time-frequency attenuation dependent in \( \gamma_k \) can be defined as a frequency-dependent motion magnification factor \( M_k \), which results in the next output of the magnified movement due to the multiplication procedure in Eq (7).

\[
\tilde{I}_m(x, t) = f(x + \sum_k (1 + M_k) \delta_k(t)) \tag{7}
\]

We assume that the observed motion \( \delta(t) \) due to the magnification factor is roughly the same as true magnified movement \( I_m(x, t) \) for the processed signal via temporary filtering \( \tilde{I}_m(x, t) \).

\[
\tilde{I}_m(x, t) = I_m(x, t) \tag{8}
\]
\[ f(x,t) + (1+M)\delta(t) \]  
\( \frac{\partial f(x)}{\partial x} = f(x+(1+M)\delta(t)) \)  
(9)

Let \( f(x) = \cos(\omega x) \) for a spatial frequency \( (\omega) \) and \( 1 + M = \beta \). We require that

\[ \cos(\omega x - \beta\omega\delta(t)) \sin(\omega x) \approx \cos(\omega x + \beta\omega\delta(t)) \]  
(10)

By using the addition law for cosine, the question becomes

\[ \cos(\omega x - \beta\omega\delta(t)) \sin(\omega x) = \cos(\omega x) \cos(\beta\omega\delta(t)) - \sin(\omega x) \sin(\beta\omega\delta(t)) \]  
(11)

The following, or roughly, may occur later.

\[ \cos(\beta\omega\delta) \approx 1 \]  
(12)

\[ \sin(\beta\omega\delta) \approx \beta\delta\omega \]  
(13)

Assume that Eq (12) and Eq (13) are less than 10% in the slight angle for \( \beta\omega\delta \leq \frac{\pi}{4} \). The relationship with the spatial wavelength of a picture structure \( (\lambda = \frac{2\pi}{w}) \) of a moving signal, \( M \) and exact increase of movement of a video motion \( \delta(t) \) are seen in the following:

\[ (1+M)\delta(t) < \frac{\lambda}{8} \]  
(14)

Although EVM technique is attractive in principle, it suffers several limitations: [44]

4. EVM is a linear approach process which linearly increases the level of noise and movement artifact with an amplification factor \( M \).

5. Only small magnification values are assisted since the overall magnification value does not surpass \( \frac{\lambda}{8} \) in Equation (14).

6. Some undesirable motions magnified during colour magnification.

7. It is highly sensitive to changing parameters and needs retrieval and error to achieve a reasonable result many times.

2.2. Phase based Video Magnification Method (PBM)
The video enlargement phase is a method for analysing and amplifying subtle movements in videos for improving EVM. A method based on a phase depends on the analysis of variations of phases which reflect the movement of the frame sequence resulting from complexly validated steering pyramid coefficients. In the phased process, all frames decomposed with octave or sub-octave bandwidth filters to multifaceted pictures in various spatial scales and directions. These changes in phase are then temporally filtered with selected frequencies that fit the movement in interest by filtering bandpass filters. Following this, phases of the temporary band smoothed with amplitude weighted spatial smoothing to increase the SNR step. The smooth stages were then expanded by the factor \( M \) and the original frame was added again. Video reconstruction applied by collapsing the pyramid to obtain the output result. As given in Equation (1), the \( f(x + \delta(t)) \) is a displaced motion function for the image intensity profile \( f \) which can be magnified by \( M, f(x + (1 + M)\delta(t)) \), as shown in Equation (6). Because the phase-based method relies on a complex-valued steerable pyramid, where the local motion can be measured and modified by modifying its phase, the displaced motion function the Fourier series decomposition can be defined as a sum of complex sinusoids [45]

\[ f(x + \delta(t)) = \sum_{w=-\infty}^{\infty} S_w(x, t) \]  
(15)

\[ S_w(x, t) = A e^{i w(x + \delta(\bar{t}))} \]  
(16)

where \( S_w(x, t) \) is a sinusoid function with an amplitude \( A \) and a phase \( w(x + \delta(\bar{t})) \) which contains the motion information. Temporal bandpass filtering \( B(x, t) \) is applied on the phase \( w(x + \delta(\bar{t})) \) to distinguish motion from the phase function of a particular temporal frequencies while assuming that a temporal filter is only used to delete a temporal DC variable \( w_x \);

\[ B_w(x, t) = w\delta(\bar{t}) \]  
(17)

Now to expand the flow, the band passed phase \( B_w(x, t) \), multiplied by factor \( M \), and this quantity is introduced into a step of the subband \( S_w(x, t) \).

\[ \hat{S}_w(x, t) = S_w(x, \bar{t}) e^{i MB_w} = A e^{i w(x + (1 + M)\delta(t))} \]  
(18)
It is clear from Equation (18) that the complex sinusoid \( \hat{S}_\omega(x, t) \) has motions exactly \( 1 + M \) times the input signal \( S_\omega(x, t) \). After that, the magnified motions in video sequences are reconstructed by collapsing the pyramid to get the final result corresponding to \( f(x + (1 + M)\delta(t)) \).

This magnification has excellent noise response characteristics compared to the linear EVM, because it translates the noise rather than magnifies it as the amplification factor is increased. To clarify this, let \( I + \sigma_n \) denote the noisy image of \( I \). The response of the noisy image can be given by

\[
\hat{S}_\omega(x, t) = A e^{i\omega(x + \delta(t))} + \sigma_n N_\omega(x, t)
\]

where \( N_\omega(x, t) \) is a reaction of \( n \) to the osteoportic indexed complex pyramid filter \( \omega \). By magnifying motion based on same procedures described in the above, Equation (19) becomes

\[
\hat{S}_\omega(x, t) = A e^{i\omega(x + (1+M)\delta(t))} + \sigma_n e^{iM\omega(t)} N_\omega(x, t)
\]

Obviously, the phase transition is the only shift after processing to a noise and noise converts dramatically over magnified. In the phase focused process, low amplitude motions that are essential to colour enlargement can be mitigated and removed by using negative magnification factor values in the range of The \([-1, 0]\). While the PBM significant enlarging factors with far less artificial effects and less noise at all spatial frequencies, there are still some limitations: [45]

1. It has a higher computational overhead: The over-completeness is determined by a factor of \( 2h/(1 - 2^{j}) \). Where \( h \) is the number of guideline bands and \( j \) is the filter number for each orientation per octave. For example, it is 12x over-complete (octave bandwidth, 4 orientations) and limits to support large magnification factor, 33x over-complete (half octave bandwidth, 8 orientations) and 56x over-complete (quarter octave bandwidth, 8 orientations).
2. The decomposition via the steerable pyramid runs about 8 times slower than the Laplacian pyramid decomposition which leads to increase the execution time.
3. High costs for implementing and building: since the complex steering pyramid has to generate a large number of filter taps and intensive frequency domain buildings that lead to spatial objects.
4. Incoherently magnified video: This happens when some video sequences have a noisy phase signal.

2.3. Fast Phase-Based Video Magnification Method (FPBM)

To overcome the over-completeness and costly implementation of the PBM, Wadhwa et al. [46] extended their work using Riesz pyramid decomposition. The Riesz pyramid is inspired by Riesz transformer used in [60, 61] with some differences. The first difference is that the Riesz transform has been carried out entirely in spatial domain to prevent wrapping of space around objects while in a frequency domain Riesz pyramid is implemented [60, 61]. The second difference is that two final filters have been used in three tap differentials [46] to speed-up the Reisz transform instead of an ideal frequency domain filter which is slower to compute [60, 61].

In the rapid PBM any frame that decomposed to several non-oriented sub-band images by an efficient decomposition in a pyramid similar to the Laplacian pyramidal decomposition and then by a fast, approximate Riesz transformation in each band to measure the step, shifted (90 degrees in two ways). The phase signals are temporally filtered to isolate the motions of interest and spatially de-noised to improve their SNR. The filtered phases are then magnified by a factor \( M \) and collapsed to obtain the output result. Riesz Transform is an invariant natural rotation, two-dimensional Hilbert transformation expression [42]. The Riesz transform has a two channels filter bank with responses (R1 and R2). The transfer functions of a pair of Riesz filters are [43]

\[
-i \frac{w_y}{|\omega|}, -i \frac{w_x}{|\omega|}
\]

These reactions together with an Image Sub-band (I) allow us in relation to the dominant orientations of each pixel to detect a quadrature pair (Q) of a non-oriented image Subband, which is 90° with an original
subband. These values \((I, R1, R2)\) are coefficients of the Riesz pyramid which can be given as spherical coordinates as below

\[
\begin{align*}
I &= A \cos(\varnothing) \\
R1 &= A \sin(\varnothing) \cos(\theta) \\
R2 &= A \sin(\varnothing) \sin(\theta)
\end{align*}
\]

(22)

where \(A, \varnothing\) and \(\theta\) represent the local amplitude, local time and local orientation. A pair of squares \(Q\) of an input signal will be used when a Riesz transformation is directed to a local dominant position \(\theta\).

\[
Q = A \sin(\varnothing)
\]

(23)

where the phase-shift between \(Q\) and local dominant orientation \(\theta\) is 90 degree. The local phase can be given as a complex number;

\[
Ae^{i\varnothing} = I + i
\]

(24)

Now, to magnify motions with the Riesz pyramid. Let \(I(x, y, t)\) denote the image intensity function of the 2D image at the time \(t\) with a slight horizontal motion \(\delta(t)\), and frequency band \(w\),

\[
I(x,y,t) = A \cos(wx, wy - \delta(t) + \varnothing)
\]

(25)

The Riesz transform (Equation 21) is applied on this 2D oriented sinusoid to give

\[
A \frac{w_x w_y}{w_x^2 + w_y^2} \sin(w_x x + w_y y - w_x \delta(t))
\]

(26)

By using Equation (23), the quadrature pair \(Q\) becomes

\[
Q(x,y,t) = A \sin(w_x x + w_y y - w_x \delta(t))
\]

(27)

where \(A\) is the local amplitude and \(w_x x + w_y y - w_x \delta(t)\) is the local phase \(\varnothing\).

The local phase \(\varnothing\) is temporally filtered to fall the DC component \(w_x x + w_y y\) and amplified by \(M\) to yield

\[
\varnothing = Mw_x \delta(t)
\]

(28)

The input signal is a phase shifted with respect to a local dominant orientation \(\theta\) to produce the following function

\[
A \cos(w_x(x - (1 + M)\delta(t)) + w_y y)
\]

(29)

In spite of advantages of the Riesz pyramid in terms of less over-completeness, execution time, and avoiding spatial wrap around artefacts associated with frequency domain compared with complex steerable pyramid, it has some issues: [46].

1. The Riesz pyramid does not work well with an image with many predominant orientations and can not distinguish two directions at the same pixel without being horizontal, specifically vertical.

2. The Riesz transform in the Riesz pyramid is not capable of maintaining input signal power compared to an optimal Riesz transformation so that some small artefacts generated.

2.4. Enhanced Eulerian Video Magnification (E2VM) Method

E2VM is a post-processing method introduced by [47] to enhance the linear EVM in terms of a higher magnification factor and less noise. It uses EVM technique as a space time-motion analyser to measure the difference between the source and expanded video by making the pixel-level movement map. Then, the movies are enhanced by warping several pixels in the path of motion mapping. Also, image scaling is used to reduce the computing time of the video processing.

To get directions for pixel-level mapping \((U, V)\) at point \((x, y)\) of 2D image, the difference between the source video \(I(x, y)\) and the magnified video \(I_m(x, y)\) are obtained using EVM method:

\[
U(x, y) = \frac{I_m(x, y) - I(x, y)}{\partial I_m(x, y) / \partial x}
\]

(30)
\[ V(x, y) = \frac{I_m(x, y) - I(x, y)}{\partial f(x, y)/\partial y} \quad (31) \]

Those instructions can be used to increase the movement in the expanded video frames with the following equation as part of the picture warping grid:
\[ I_m(x, y) = I(x + \rho(x, y) U(x, y) + \rho(x, y) V(x, y)) \quad (32) \]
where \( \rho(x, y) \) is a smooth matrix to further change the input video magnification to smooth the warping grid boundary through mean processing. Elements of \( \rho(x, y) \) in picture borders close to 0 are set, allowing motion noises from the EVM to smooth and delete.

Although E2VM has advanced over the EVM in terms of higher magnification factor and less noise, it also suffers from some limitations: [47]

1. It takes more about 15–20% execution time than the EVM.
2. Some magnification specifications may be lost during warping process.
3. Limitations of the EVM technique restrict the results of the E2VM.

The performance comparison and main differences for all video magnification methods are summarised in Table 1.

| Table 1. Comparison of results of the process of video enlarging. |
|--------------------------|-----------------|----------------|-----------------|
| **EVM**                  | **PBM**         | **FPBM**       | **E2VM**        |
| Decomposition            | Laplacian pyramid | Complex steerable pyramid | Riesz pyramid | Laplacian pyramid |
| Noise                    | Magnified       | Translated     | Translated      | Minimised via post-processing |
| Over-completeness        | 3 \( \frac{1}{4} \) image | \( 2b/(1 - 2^2) \) (With octave bandwidth three times slower than EVM, 2 orientations) | \( \approx20\% -80\% \) faster than PBM (2 orientations, octave bandwidth) | \( \approx15\% -20\% \) slower than EVM |
| Magnification factor     | Support small magnification factor* assistance with filter sub-octave bandwidth | High magnification factor assistance | medium magnification factor assistance |
| Exact for                | Linear ramps    | Sinusoid       | Sinusoid        | Linear ramps      |

* A step method with broad magnification factors (octave filter length, 2 orientations) does not help.

3. **Objective Video Quality Parameters**

The objective parameters for video quality are quantitative indicators that can predict perceived video quality automatically. Depending on the source video (reference video), these parameters can be grouped into three groups: parameters of maximum reference quality, non-reference quality parameters and reduced reference quality parameters.

As no single parameter can cover all image properties and performs well under various suppositions. This review used 10 objective parameters classified into three categories of full reference quality: First group, picture intensity and mathematical models (e.g. PSNR), mean square error (MSE). Secondly group, parameters based on characteristics of the human visual system examples; visual signal to noise ratio (VSNR) [51], weight signal to noise ratio (WSNR) [53], universal quality index (UQI) [56], structural similarity index (SSIM) [57], noise quality measure (NQM) [52] and feature similarity (FSIMc) [58]. Thirdly category, parameters based on natural scene statistics examples; information fidelity criterion (IFC) [55] and visual information fidelity (VIF) [54]. When MSE is near to zero, the PSNR, VSNR, WSNR and NQM calculated in decibels. The UQI, SSIM, VIF and FSIMc range of values \([0, 1]\) is near one, while IFC ranges between zero (no fidelity to data) and infinity (perfect fidelity to information).
4. Experimental Results & Discussion

The four source videos with different resolutions were taken and also the frame rate was taken as comparisons in the analysis of the data. [44] The videos used mainly in the relevant studies are 301 and 60 fps, respectively, at the frames and frame rate of one video (baby1) taken by the camera "Nikon D5300" with the resolution of 960 x 540-pixel [62]. Many of the magnification methods mentioned in Section 2 have been applied to these sources. The baby1 video filmed with a 960 x 544-pixel "Canon EOS 60D" camera with 301 and 30, respectively, frames and frame rates. The video captured from the 512 x 384-pixel resolution sensor of the "Casio Exilim EX F1" is 1000 and 300 fps respectively at frames and frame rates. The guitar video captured by the 432 x 192-pixel "Casio Exilim EX F1" camera is 300 and 600 fps respectively in frame and frame rate. These videos are encoded with H.264 in MPEG-4 format. For each magnification method addressed, 10 image parameters have been utilised for the purposes of checking the video quality of the magnified videos compared to source images (reference images) and selecting which can provide better performance.

In Figure 1, A baby1 video has been magnified with the same magnification parameters (M=20, cutoff rate=16, and 0.4–0.05 Hz B.P.F) by all mentioned magnification methods to achieve a variety of outputs. Even with human vision, the PBM, FPBM and E2VM were superior to EVM at the noise level.

To determine the quality and compare the source video of a magnified baby1 video from each of the modules discussed, ten parameters of the video quality utilized to compare and select which magnification method gives good quality outcomes.

In the frame sequences between the magnified EVM video and the source video, the consistency parameters are applied for the first column and applied between the magnified video from the dependent system and the source video for a second column as shown in Table 2. In this table, we independently calculated the mean values of these parameters for all frame sequences and their ranks (the highest “1” and the lowest “4”) as shown in this table, where a better-ranked method highlighted in underline. From this table, the E2VM method had better values for parameters in terms (i.e. SNR, MSE, VSNR, WSNR, SSIM, IFC and FSIMc), while the PBM outperformed in NQM and a FPBM outperformed in UQI.

![Figure 1. A sample image obtained from magnified video (baby1) using (a) EVM [44], (b) PBM [45], (c) FPBM [46] and (d) E2VM [47].](image-url)
Table 2. Comparison of the video quality parameters for the magnified video (baby1).

|   | EVM          | PBM          | FPBM         | E2VM         |
|---|--------------|--------------|--------------|--------------|
| 1 | PSNR 31.208 | 32.892       | 31.027       | 34.911       |
| 2 | MSE 49.199   | 41.166       | 41.198       | 41.023       |
| 3 | VSNR 18.682  | 21.327       | 21.268       | 25.627       |
| 4 | WSNR 27.027  | 30.635       | 26.635       | 30.644       |
| 5 | UQI 0.4147   | 0.6170       | 0.6290       | 0.6121       |
| 6 | SSIM 0.8823  | 0.9477       | 0.9515       | 0.9602       |
| 7 | IFQ 1.4038   | 1.8614       | 2.1299       | 2.2291       |
| 8 | VIF 0.4717   | 0.4723       | 0.5663       | 0.5932       |
| 9 | NQM 18.877   | 22.756       | 22.682       | 21.387       |
| 10| FSIMc 0.8961 | 0.9663       | 0.9743       | 0.9820       |

In Figure 2, we also magnified baby2 video with the same previous assumptions and obtained four outputs from four different magnification methods.

![Magnified video sample images](image)

Figure 2. A magnified video sample image (baby2) via (a) EVM [22], (b) PBM [45], (c) FPBM [46] and (d) E2VM [47].

In Table 3, video quality parameters also applied on the magnified videos from each discussed method to obtain four columns on as shown in Table 3, where the rank of mean values of the video quality parameters according to the best “1” to the worst “4” presented in this table. In addition, it is obvious, from the results of this table that all the other methods over-performed in all parameters by an E2VM and each other in different degrees by other methods.
Table 3. Comparison for magnified video (baby2) the video quality parameters.

|     | EVM       | PBM       | FPBM      | E2VM      |
|-----|-----------|-----------|-----------|-----------|
| 1   | PSNR      | 25.071 (2) | 24.039 (4) | 24.707 (3) | 30.726 (1) |
| 2   | MSE       | 203.329 (2) | 256.175 (4) | 220.106 (3) | 55.016 (1) |
| 3   | VSNR      | 11.246 (4) | 11.726 (3) | 12.612 (2) | 24.637 (1) |
| 4   | WSNR      | 24.754 (4) | 26.295 (3) | 27.528 (2) | 37.493 (1) |
| 5   | UQI       | 0.6320 (4) | 0.7006 (3) | 0.7047 (2) | 0.8951 (1) |
| 6   | SSIM      | 0.8703 (2) | 0.8378 (4) | 0.8530 (3) | 0.9553 (1) |
| 7   | IFC       | 2.9217 (2) | 2.7935 (3) | 2.7687 (4) | 5.0077 (1) |
| 8   | VIF       | 0.4615 (2) | 0.3584 (4) | 0.3786 (3) | 0.6286 (1) |
| 9   | NQM       | 13.422 (4) | 15.840 (3) | 17.574 (2) | 24.594 (1) |
| 10  | FSIMc     | 0.8773 (4) | 0.8983 (3) | 0.9116 (2) | 0.9911 (1) |

In Figure 3, the camera video was magnified by using all discussed magnification methods with the same magnification parameters (M= 100, cutoff rate =15 and 36–62 Hz B.P.F) to achieve an output.

![Figure 3. A magnified video (camera) image sample via (a) EVM [44], (b) PBM [45], (c) FPBM [46] and (d) E2VM [47].](image)

In Table 4, video quality parameters and their ranks for each discussed method according to the best “1” to the worst “4” presented in this table. E2VM is obvious in all parameters except for NQM which has the best PBM, whereas other methods can only be superior in consistency parameters.
Table 4. Comparison of the magnified video quality (camera) parameters.

|   | EVM       | PBM       | FPBM      | E2VM      |
|---|-----------|-----------|-----------|-----------|
| 1 | PSNR 28.321 (2) | 25.265 (4) | 26.489 (3) | 34.258 (1) |
| 2 | MSE 95.530 (2)  | 193.553 (4) | 146.067 (3) | 24.410 (1)  |
| 3 | VSNR 21.958 (3)  | 21.958 (3)  | 24.985 (2)  | 30.873 (1)  |
| 4 | WSNR 28.908 (2)  | 28.908 (2)  | 26.861 (3)  | 31.153 (1)  |
| 5 | UQI 0.7242 (3)   | 0.6863 (4)  | 0.7316 (2)  | 0.8481 (1)  |
| 6 | SSIM 0.8790 (3)  | 0.8433 (4)  | 0.8844 (2)  | 0.9662 (1)  |
| 7 | IFC 4.2528 (2)   | 2.9603 (4)  | 3.7644 (3)  | 6.0174 (1)  |
| 8 | VIF 0.5174 (2)   | 0.3447 (4)  | 0.4458 (3)  | 0.7287 (1)  |
| 9 | NQM 16.136 (4)   | 23.845 (1)  | 20.578 (3)  | 23.375 (2)  |
|10 | FSIMc 0.9185 (4) | 0.9361 (5)  | 0.9566 (2)  | 0.9882 (1)  |

In Figure 4, guitar video was magnified by using all magnification methods with the same magnification parameters ($M = 50$, cutoff rate =10 and 72–92 Hz B.P.F) to achieve an output.

![Figure 4](image-url)

Figure 4. A sample picture of magnified video (guitar) via (a) EVM [44], (b) PBM [45], (c) FPBM [46] and (d) E2VM [47].

In Table 5, video quality parameters and their ranks presented in this table. The table shows that the E2VM method is outperformed by all video parameters, but only by quality parameters can other methods outperform each other.
Table 5. Comparison of the video quality parameters for the magnified video (guitar).

|   |  EVM       |  PBM       |  FPBM      |  E2VM      |
|---|------------|------------|------------|------------|
| 1 | PSNR       | 32.642 (2) | 24.788 (4) | 24.929 (3) | 35.528 (1) |
| 2 | MSE        | 35.201 (2) | 216.243 (4)| 209.804 (3)| 18.019 (1) |
| 3 | VSNR       | 27.369 (2) | 23.567 (4) | 26.216 (3) | 34.179 (1) |
| 4 | WSNR       | 31.889 (3) | 33.456 (2) | 27.937 (4) | 36.624 (1) |
| 5 | UQI        | 0.8691 (2) | 0.7231 (4) | 0.7546 (3) | 0.9236 (1) |
| 6 | SSIM       | 0.9444 (2) | 0.8534 (4) | 0.8568 (3) | 0.9701 (1) |
| 7 | IFQ        | 5.9320 (2) | 4.6214 (4) | 5.3249 (3) | 6.9935 (1) |
| 8 | VIF        | 0.6205 (2) | 0.4842 (4) | 0.5394 (3) | 0.7444 (1) |
| 9 | NQM        | 23.284 (2) | 20.284 (4) | 20.293 (3) | 28.330 (1) |
|10 | FSIMc      | 0.9749 (2) | 0.9291 (3) | 0.9206 (4) | 0.9864 (1) |

The runtime is a time-period needed for a whole frame sequence of a source video to be enlarged. Time of execution varies and relies on two variables, such as source video resolution and frame rate per second. The execution time of each magnifying method tested on the Intel core i7, 3.2GHz CPUs, 8 GB RAMs, and Windows 10 operating systems for four source videos and calculated via Matlab R2019b.

In Figure 5, a magnification process (software) via PBM is slower by about 2–3 times than the EVM, while FPBM and E2VM are slower by about 27% and 15% than EVM, respectively. This means that E2VM can accomplish the magnification process with closer execution time to EVM than other methods. However, the magnification process-based EVM still requires a significant amount of time for the processing video frames captured by high-resolution camera with high frame rates.

Although this review summarised the performance of the video magnification methods regarding to the internal structure, limitations, video quality and execution time, the further study still needed to test and compare these methods with different magnification factors, temporal information or with other video quality parameters that can operate with moving images.

Figure 5. Execution time comparison in seconds of the video magnification methods.
5. Conclusions
This paper presented four methods for video magnification (i.e. EVM, PBM, FPBM, and E2VM) to find subtle observations that cannot be observed directly using the human eye. It obvious that other methods for the video magnification outperform EVM in terms of performance; support large magnification factor, noise level and video quality. The E2VM method has more advantages than other methods in aspects of performance, video quality parameters and execution time. In addition, it is the better value of the most video quality parameters tested on four source videos. Furthermore, E2VM is good execution time (15–20% slower than EVM) in comparison with other methods. In the other hand, the EVM still takes a less amount of time compared with other methods. However, all methods take substantial time to process videos captured by a high-resolution camera with high frame rates. Moreover, the EVM is a principle for all methods, while, any problem in the EVM affects other methods. In future work, it is a great need for new magnification method that can be implemented in less time than EVM. In addition, it has better video quality parameters also less noise than other methods.

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