

Adaptive Eulerian Video Magnification Methods to Extract Heart Rate From Thermal Video

Stephanie L. Bennett¹, Member, IEEE, Rafik Goubran^{1,3}, Fellow, IEEE.

¹Department of Computer and Systems Engineering
Carleton University
Ottawa, Canada
sbennett@sce.carleton.ca

Frank Knoefel^{2,3}, M.D.

²Department of Family Medicine, University of Ottawa

³Brûyère Continuing Care
Ottawa, Canada
fknoefel@bruyere.org

Abstract— The world's expanding and aging population has created a demand for inexpensive, unobtrusive, automated healthcare solutions. Eulerian Video Magnification (EVM) aids in the development of these solutions by allowing for the extraction of physiological signals from video data. This paper examines the potential of thermal video in conjunction with EVM to extract physiological measures, particularly heart rate. This paper also proposes an adaptive EVM approach to amplify the desired signal, while avoiding noise amplification. A subject, wearing a textile sensor band collecting ECG, sat still while both a thermal camera and an iPad camera captured video. The iPad video was subjected to EVM, using a wide bandpass filter and low magnification factor. Mean intensity signals for five Regions of Interest (ROIs) were then calculated to extract a signal representing heart rate. The ECG signal was used to validate the ROI resulting in the mean intensity signal best representing heart rate. The thermal video was then subjected to EVM using the same wide bandpass filter and the identified ideal ROI mean intensity post-processing. This signal was compared to the enhanced iPad video mean intensity signal to verify the correct signal was extracted. The original thermal video was subjected again to EVM processing and ROI mean intensity post-processing, this time using an adapted, targeted narrow bandpass filter. Results indicated that thermal video, in conjunction with the proposed adapted EVM method and ROI post-processing can reveal physiological signals like heart rate and limit the potential of revealing an amplified noise signal.

Keywords—Eulerian Video Magnification, Image Processing, Thermal Imaging, Physiological Signals.

I. INTRODUCTION

As the world's population both expands and ages, healthcare organizations fight to adapt [1]. The financial strain accompanying these population changes exasperates already understaffed hospitals and overflowing patient volumes [1]. As a result, there is a large market for inexpensive, unobtrusive, automated healthcare solutions. These solutions are often sensor based monitoring systems providing continuous patient monitoring and automated patient assessments. There is a need for these monitoring systems to be inexpensive, compact and multi-functioning; providing measurement of several biological signals with one device.

This research was supported by AGE-WELL NCE Inc., a member of the Networks of Centres of Excellence program, as well as the National Sciences and Engineering Research Council (NSERC) of Canada.

Eulerian Video Magnification (EVM) is a procedure developed by the Massachusetts Institute of Technology (MIT) that works towards device versatility by allowing a device as small and widely available as a smart phone to measure biological signals by simply capturing video footage of a subject [2]. This procedure breaks a video down spatially and temporally to amplify variations occurring within a specified frequency. The result is the enhancement of motion or color variations that cannot be seen by the human eye. Research has shown this procedure (and similar methods) can use video footage to reveal biological signals including adult heart rate and respiratory rate, infant heart rate and respiratory rate, pulse transit time, finger vein liveness detection, among others [2]-[5]. Recently, EVM has been examined in relation to thermal video. Thermal video in conjunction with EVM and post-processing has been shown to successfully reveal respiration rates and respiration patterns indicative of obstructive sleep apnea [6]. Thermal cameras have the potential to reveal biological signals that regular cameras may not be able to. For example, the effects of pressure on blood flow can be seen using a thermal camera, but may not be revealed using regular video [7]. The potential for a thermal camera to provide physiological signal measurement is further explored in this paper by examining whether or not heart rate can be extracted from Eulerian enhanced thermal video.

While EVM has been shown to successfully and unobtrusively measure biological signals, the drawback of EVM is that it can significantly amplify noise as the magnification factor increases [8],[9]. This, coupled with the inherent noise occurring during regular and thermal video acquisition leads to enhancement issues. When using EVM with a narrow bandpass filter, one can extract any frequency within the passband. This can lead to the amplification of noise alone and the false attribution of this signal to blood flow and heart rate. This paper aims to mitigate this effect by developing an adaptive EVM approach. This approach first employs a wide bandpass filter with a low amplification factor to identify an underlying signal, then re-processing, employing a narrow bandpass filter with a higher amplification factor to reveal a signal representative of subject heart rate, not amplified noise.

II. METHODS

A. Equipment

For experimentation, a FLIR A-Series Infrared Camera was used, as well as a Hexoskin smart shirt and an associated data collection device. In addition, a laptop, an iPad and a smart phone were used to control and capture data.

The FLIR A-Series infrared (IR) camera captures temperature within the range of -20.0°C to 350.0°C at an accuracy of $\pm 2\%$ and sensitivity of <0.05°C [10]. The IR camera has a resolution of 640x480 and captures thermal video (at 60 Hz) as well as thermal images [10]. The Hexoskin smart shirt is a garment containing various textile sensors for capturing biological information [11]. It is connected to a small data bus that both gathers and transmits this information to a smart device.

FLIR software was downloaded on the laptop, which was used to control thermal data acquisition. The Hexoskin application was downloaded on the smart phone, which was used to control the smart shirt, and the iPad was used to capture video with a resolution of 768x1024, at a frame rate of 30Hz. For the duration of this paper, the iPad video will be referred to as the ‘light video’ to distinguish regular video from thermal video.

B. Experimental Conditions

According to the guidelines set out by the American Academy of Thermology [12], thermal experiments involving humans often require the best possible control of atmospheric interference. Efforts were made to mitigate these atmospheric effects as much as possible.

The room in which experimentation occurred was set to a temperature of 23°C and was measured to have a humidity of 33%. The room was larger than 8ft x 10ft; large enough to maintain a homogenous temperature. The room did not utilize fluorescent lights, nor were any lights on during experimentation. The door to the room was closed to prevent outdoor drafts. Before any data collection, the subject was given an equilibrium period of 15 minutes and refrained from exercise, sun bathing, physical therapy and the use of creams.

C. Experimental Procedure

After a 15 minute equilibrium period, the subject put on the Hexoskin smart shirt, ensuring that the two textile sensors (at the thoracic and abdomen areas) were in contact with the skin. The Hexoskin data collection device was placed in a designated pocket in the shirt. The subject sat in a chair, as still as possible, throughout experimentation. This was important, as subject motion can affect EVM results.

The thermal camera was set up on a tripod to face the subject. The iPad capturing light video was also set-up to face the subject from the same distance away (but with different zoom capabilities). The smart phone was held in a third party’s hand to minimize subject motion and to stop and start the smart shirt without introducing thermal interference. The equipment start times were staggered due to the manual nature of the laptop and iPad. This was accounted for by having the subject

grab the thoracic textile band and move it in a vigorous manner. This introduced noise in the ECG signal and a simultaneous visual cue in the thermal and light video recordings. Following this movement, the subject was still for approximately one and half minutes. This paper considers ten seconds of this data.

D. Eulerian Video Magnification

Both thermal and light video data were subjected to EVM. This procedure breaks each frame of a video into pixels, determines its color value, and amplifies temporal variations occurring within a specified frequency band. The following provides a brief overview of the Eulerian enhancement procedure.

- A video is first spatially decomposed and a Laplacian pyramid is computed [2]. This results in the breakdown of this video into several spatial levels; each pixel within each level is subjected to temporal processing. This processing extracts each pixel’s time series and applies a bandpass filter in order to extract frequency bands of interest [2]. Once the frequency band of interest is extracted, it is magnified by a magnification factor, α , and added back to the original signal. The spatial pyramid is then collapsed, resulting in the desired output video.
- The EVM method can be used for motion amplification as well as color amplification and as such, is customizable to the user’s needs. The user specifies several parameters including the filter type, the frequency band of interest and the magnification factor.

E. Light and Thermal Video Data Analysis

This paper explores the extraction of heart rate from thermal video. It uses a simultaneous ECG signal and light video in conjunction with EVM to verify thermal video results. Because of the presence of noise in the videos, EVM for color amplification using a narrow bandpass filter (suggested in [2] for best results) results in an amplified color variation signal within any narrow passband. This means one can falsely report a heart rate signal. This paper looks to solve this problem by introducing an adaptive EVM method. This method is detailed in the following.

- The light video was first subjected to EVM, using a wide passband and a relatively low magnification factor (all EVM parameter values are specified in Table I). The enhanced output video was then examined to see if the correct heart rate signal could be extracted despite the use of a wide passband.
- Several Regions of Interest (ROIs) were created to determine if the correct heart rate could be extracted and if so, where the ideal ROI would be. Five ROIs were created; one enclosing the entire face, another enclosing the subject’s right cheek, another enclosing the subject’s forehead and the last two enclosing an area on the subject’s chest and arm. These ROIs are depicted in Figure 1.

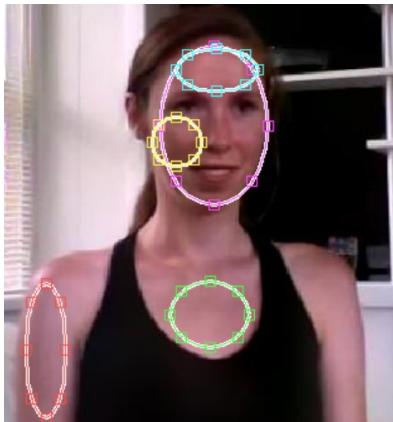


Fig. 1. Depiction of the light video ROIs.

- The enhanced light video color intensity was examined within each ROI. The minimum, mean and maximum intensities were calculated temporally, within each ROI. Each of these resulting signals was filtered with a fourth-order, zero-phase, Butterworth lowpass filter and were then normalized and examined.
- The filtered mean intensity signals were compared amongst each other and with the ECG signal. The best performing filtered mean intensity signal was chosen to be the signal that best correlated with the ECG signal. This signal resulted from the ROI enclosing the subject's chest.
- The thermal video was then subjected to EVM, using the same parameters as for the light video; a wide passband and relatively low magnification factor. The enhanced thermal output video was examined at the same region that revealed an enhanced light video mean intensity signal representative of the true heart rate. This thermal video ROI is depicted in Figure 2.



Fig. 2. Depiction of the thermal video ROI.

- The enhanced thermal mean intensity was calculated within the ROI temporally; this signal was filtered using a fourth-order, zero-phase, Butterworth lowpass filter. The filtered mean intensity signals resulting from the same ROI in the light and thermal videos were compared to ensure correlation.

- The original thermal video was subjected again to EVM, this time using a narrow bandpass filter and a higher magnification factor. The narrow passband was targeted; it was chosen to be within the former wide passband, and to enclose the frequencies extracted from the subject's chest, using the wide passband. The narrow bandpass filter enhanced thermal video was examined as before; the chest ROI mean intensity signal was found, filtered and compared to the ECG signal to ensure correlation.

F. Biosignal Data Analysis

- Biological signals captured by the Hexoskin smart shirt include, but are not limited to ECG leads I, II and III, heart rate, breathing rate and acceleration in the x, y and z directions. This paper is concerned only with the ECG lead I signal. This signal was obtained from the Hexoskin data collection device and imported to Matlab.
- The ECG signal was low pass filtered, normalized and aligned with the light and thermal video data to validate findings.

III. RESULTS

The EVM method successfully enhanced temporal color variations in both thermal and light video. Due to inherent noise in the thermal and light videos (occurring during acquisition), EVM, using a narrow bandpass filter can reveal temporal color variations that do not represent heart rate. An example of this is depicted in Figure 3. The light and thermal videos were subjected to EVM using a narrow bandpass filter with cut-off frequencies $f_{low} = 1.33$ Hz (80 beats per minute), $f_{high} = 1.50$ Hz (90 beats per minute) and an amplification factor of 100. It can be seen that the light and thermal video mean intensity signals depict the same average frequency of $f = 1.43$ Hz (86 beats per minute), where the ECG signal reveals that the actual heart rate is at a frequency of $f = 0.88$ Hz (53 beats per minute).

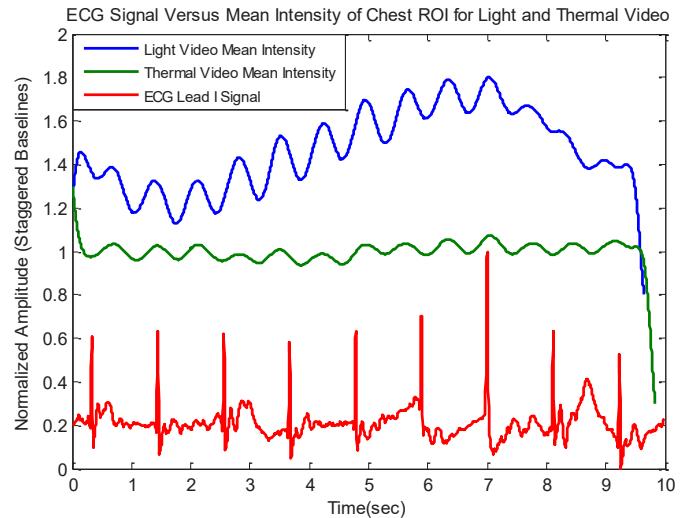


Fig. 3. Light and thermal video ROI mean intensity signals (EVM bandpass filter 1.33 to 1.5 Hz) versus ECG signal.

The adaptive EVM approach proposed in this paper aims to mitigate this effect by first using a wide bandpass filter with a low amplification factor to pick up the correct signal representing heart rate, then adapting the EVM filter to be a narrow bandpass filter including the detected frequencies and re-processing the original video with the adapted filter to reveal the true heart rate signal. This paper also examines the potential for thermal video in conjunction with EVM processing to reveal a subject's heart rate. First, the light video was subjected to EVM using a wide bandpass filter, the parameters for which can be seen in Table I, and post-processing to determine an ideal ROI revealing the true heart rate signal. The best performing ROI was the area enclosing the subject's chest; the resulting chest ROI mean intensity signal is depicted in Figure 4, plotted with the ECG signal. It can be seen there is a strong correlation between the signals; both oscillate at $f = 0.9$ Hz (approximately 54 beats per minute).

TABLE I. EVM PARAMETER VALUES: WIDE PASSBAND

Parameter	Light Video	Thermal Video
Low frequency bound of the band-pass filter	0.5 Hz	0.5 Hz
High frequency bound of the band-pass filter	1.5 Hz	1.5 Hz
Magnification Factor	75	75
Frame rate	30 Hz	60 Hz
Attenuation factor	0.1	0.1

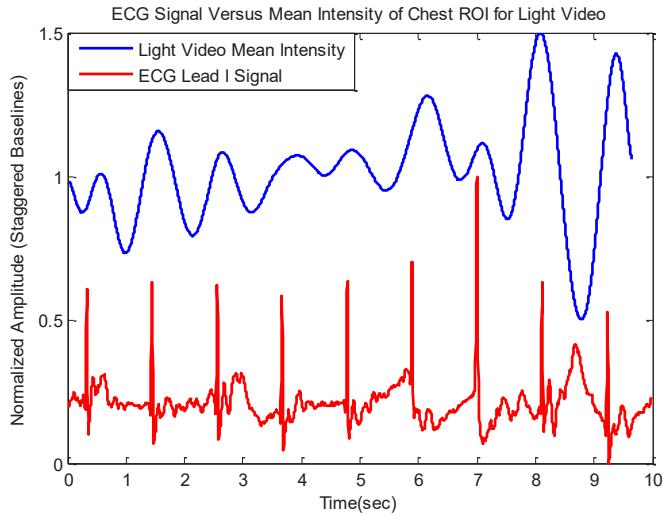


Fig. 4. Light video ROI mean intensity signal (EVM bandpass filter 0.5 to 1.5 Hz) versus ECG signal.

The thermal video was then subjected to EVM, using the same parameters as for the light video, detailed in Table I. The identified ideal ROI was used to extract the mean intensity signal representing the heart rate. This signal was compared to the previously extracted and validated enhanced light video mean intensity signal. This comparison is depicted in Figure 5. While there are some variations between signals, the correlation is visually clear.

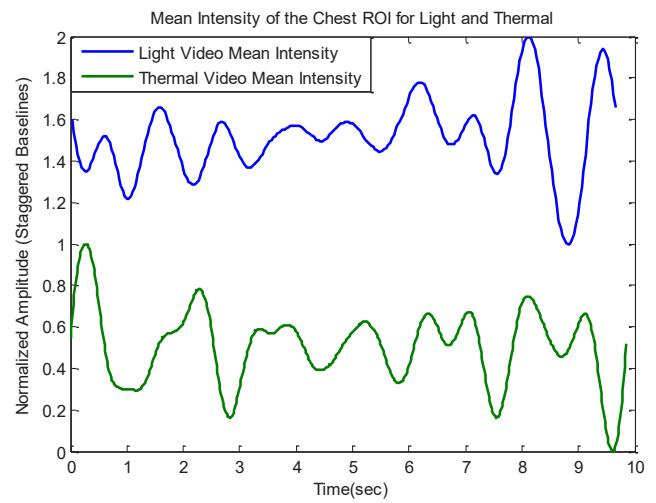


Fig. 5. Light video ROI mean intensity signal versus thermal video ROI mean intensity signal (EVM bandpass filter 0.5 to 1.5 Hz).

The frequencies of the extracted mean intensity signals were in the range of $f_{\text{thermal}} = 0.8$ Hz (48 heart beats per minute) $f_{\text{light}} = 0.9$ Hz (54 heart beats per minute). The previous EVM filter was then adapted to enclose these frequencies tightly. The original thermal video was again subjected to EVM processing, this time using a narrow bandpass filter and a higher magnification factor. The EVM parameter values for this adapted filter can be seen in Table II.

Following EVM processing, the chest ROI mean intensity signal was again calculated. This signal was compared with the ECG signal, both of which are depicted in Figure 6. It can be visually and quantitatively confirmed that the extracted thermal signal representing heart rate resulting from the EVM narrow band pass filter displays a strong correlation with the ECG signal; again both signals oscillate at $f = 0.9$ Hz (approximately 54 beats per minute).

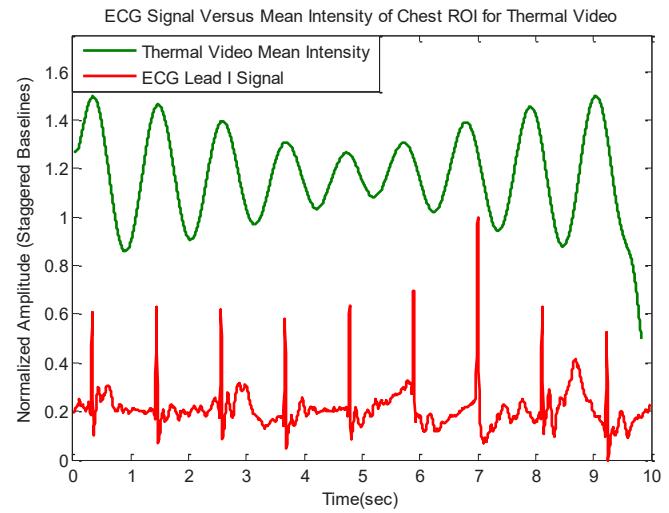


Fig. 6. Thermal video ROI mean intensity signal (EVM bandpass filter 0.75 to 1 Hz) versus ECG signal.

TABLE II. EVM PARAMETER VALUES: NARROW PASSBAND

Parameter	Thermal Video
Low frequency bound of the band-pass filter	0.75 Hz
High frequency bound of the band-pass filter	1.0 Hz
Magnification Factor	120
Frame rate	60 Hz
Attenuation factor	0.1

IV. DISCUSSION

This paper examined the potential for thermal video in conjunction with EVM processing to reveal a subject's heart rate. This paper also proposed an adaptive EVM method to avoid the amplification of noise and the false attribution of a noise signal to blood flow.

The subject wore a Hexoskin smart shirt to capture biological signals, namely ECG, while both a light camera and a thermal camera simultaneously captured video of the subject sitting very still. The light video was subjected to EVM processing using a wide bandpass filter with a relatively low amplification factor. This enhanced video was analyzed to determine an ROI most likely to reveal the true heart rate. Five ROIs were created and the mean intensity signal was found for each enclosed area. The ROI resulting in the signal oscillating at a frequency closest to that of the ECG signal was the ROI enclosing the chest. This was an interesting result, considering that this ROI was the closest to the heart. When the chest ROI mean intensity signal was compared with the ECG signal, the correlation was visually identifiable. This suggested that, using EVM with a wide bandpass filter and an ROI at the chest, one may be able to identify the heart rate and not amplified noise. This theory was tested using the thermal video; following EVM processing with the same wide bandpass filter, one ROI was created enclosing the subject's chest and the mean intensity signal was extracted. This signal was compared with the enhanced light video mean intensity signal. The correlation, while not perfect was still visually identifiable. This validated that the oscillations were not simply amplified noise; the EVM and post-processing were therefore repeated with the thermal video, using a narrow passband and higher amplification rate. The resulting narrow passband enhanced thermal mean intensity signal displayed a strong correlation with the ECG signal.

These results suggest that thermal video in conjunction with EVM and post-processing can reveal a signal representative of heart rate. These results also indicate that when the heart rate is unknown, an adaptive method can be applied wherein one employs EVM with a wide bandpass filter to identify the signal of interest, then re-process, employing a targeted narrow bandpass filter to amplify the signal of interest, rather than simply amplifying noise. These results further indicate that should one want to find an unknown heart rate

using the proposed adaptive EVM method, the mean intensity signal should be obtained from an ROI enclosing the chest area of the subject under examination.

V. CONCLUSION

This paper demonstrated the potential of the proposed adaptive EVM method to extract an existing physiological signal and not simply an amplified noise signal. Furthermore, this paper demonstrated the potential for thermal video in conjunction with the proposed adaptive EVM methods to be used in the extraction of physiological signals.

Future work involves the inclusion of several subjects, automation of the filter adaptation from a wide to narrow passband, the involvement of motion capture and motion compensation and the examination of physiological signals other than heart rate.

REFERENCES

- [1] M. Caley, and S. Khesh, "Estimating the future healthcare costs of an aging population in the UK: expansion of morbidity and the need for preventative care," *Journal of Public Health*, vol. 33, no. 1, pp. 117-122, June 2010.
- [2] H. Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. Freeman, "Eulerian video magnification for revealing subtle changes in the world," *ACM Trans. on Graphics (TOG)*, vol. 31, no. 4, pp. 651-658, July 2012.
- [3] X. He, R. A. Goubran, and X. P. Liu, "Using Eulerian video magnification framework to measure pulse transit time," in *Proc. IEEE Int. Symp. on Medical Measurement and Applications (MeMeA)*, Lisbon, Portugal, pp.1-4, June 2014.
- [4] D. Alinovi, L. Cattani, G. Ferrari, F. Pisani, and R. Raheli, "Spatio-temporal video processing for respiratory rate estimation," in *Proc. IEEE Int. Symp. on Medical Measurement and Applications (MeMeA)*, Turin, Italy, pp.12-17, May 2015.
- [5] R. Raghavendra, M. Avinash, S. Marcel, and C. Busch, "Finger vein liveness detection using motion magnification," in *Proc. IEEE Int. Symp. On Biometrics Theory, Applications and Systems (BTAS)*, pp.1-7, September 2015.
- [6] S. L. Bennett, R. Goubran, and F. Knoefel, "The detection of breathing behavior using Eulerian-enhanced thermal video," in *Proc. IEEE Eng. Med. Biol. Soc. (EMBC)*, pp.7474-7477, August 2015.
- [7] S. L. Bennett, R. Goubran, and F. Knoefel, "Measurements of change in thermal images due to applied pressure," in *Proc. IEEE Int. Symp. on Medical Measurement and Applications (MeMeA)*, pp.30-35, May 2015.
- [8] W. Neal, M. Rubinstein, F. Durand, and W. T. Freeman, "Phase-based video motion processing," *ACM Trans. Graph.*, vol. 32, no. 4, pp. 1-9, July 2013.
- [9] L. Liu, L. Lu, L. Jingjing, J. Zhang, and X. Chen, "Enhanced Eulerian video magnification," in *Proc. IEEE Int. Congress on Image and Signal Processing (CISP)*, pp.50-54, Oct. 2014.
- [10] FLIR Instruments. *Introducing the FLIR E4, E5, E6 and E8 Infrared Cameras with MSX* [website]. <http://www.flir.com/instruments/display/?id=61194>
- [11] Hexoskin. *Hexoskin Full Women's Kit* [website]. <http://www.hexoskin.com/collections/all/products/hexoskin-performance-optimization-toolkit-women-s>
- [12] American Academy of Thermology. *Guidelines for Breast Thermology* [website]. <http://aathermology.org/organization/guidelines/guidelines-for-breast-thermology>.