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# MOBILE IMAGING FOR MONITORING AND EARLY WARNING OF CARDIOVASCULAR DISORDERS IN NEO-NATAL

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**Abstract**

Due to unavailability of basic health care, every year millions of infants die in developing countries because of respiratory and cardiac diseases. Most of the present mobile or mobile based health monitoring devices is inefficient and unavailable to people in developing countries that are largely dependent on the conventional monitoring systems, which are immobile, inaccessible and costly for them. **Minder** is the project being developed, based on advanced image processing algorithm proposed as Eulerian Video Magnification (EVM). The algorithm utilizes a PC based Matlab implementation to magnify videos. The paper and the project, discuss a complete mobile based system to monitor the vitals of neo-natal and infants and further processing techniques implemented over the EVM for real time face-detection and tracking, cardiac pulse estimation, display of magnified blood flow, signal validation, test results and discussion on future prospects of the application.

**Keywords:** Eulerian Video Magnification, Spatial Filtering, Temporal Filtering, Detrending

**Introduction**

Worldwide millions of infants die due to curable respiratory disorders like asphyxia, pneumonia, respiratory syncytial virus, neonatal respiratory distress syndrome, bronchiolitis and other cardio-vascular disorders. The scenario is dour in developing nations as majority of people have no access to proper health care systems, are remotely placed or cannot afford medical bills. The available mobile diagnostic devices usually targets people in developed nations and hence are either unavailable or too expensive for an average person to buy in a developing world. The present photo-plethysmographic[1]diagnostic instruments available are touch based and thus is ill suited for neo-natal and infant monitoring, as they create discomfort and hinder natural movements of the children. Minderon the other hand isa touch-lessremote monitoring, standalone mobile application aimed at monitoring the vitals of an infant like heartbeats, respiration rate andblood oxygen levels. With its first phase of implementation, it recognizes a human face and then implements Eulerian video magnification[2] in the frequency range of 0.4-4 Hz (24-240 beats) with an IIR filter, time duration between magnified color variations due to blood flow in face is then used to deduce the heartbeat[3,4]. This is then monitored and any undesired reading is relayed in form of an alarm, a record of overnight heartbeat rating is also kept, so any repetitive patterns relating to a respiratory or cardiac disorder can be diagnosed at the earliest. As EVM is a comparatively new method of revealing temporal variations in a video invisible to perceive by human eyes, very less work has been done over it. Most of the work is done on the PC based system, using Matlab. This paper discusses the OpenCV[5] implementation of Eulerian video magnification for operational portability over mobile devices. Exploiting the increased processing capabilities of today's smart phones, integrated wearable or standalone software systems will be more popular than independent wearable health diagnostic gadgets due to their all-time availability and cost efficiency.

**Methodology**

**Face detection**

Cascade-Classifier class which is used to detect objects in a video stream in Open CV is used to detect human face. There are two mainstream classifiers Haar[6] and Local Binary Pattern[7]are used. Due to the faster processing speed of local binary pattern filter we trade off 10-15% accuracy in face detection with Haar. Local binary pattern deals with integer calculations while Haar uses float calculations which are inefficient on mobile devices. Also the minimum size of face detector was set to 40% of the frame width and height, as the system usually monitors sleeping subjects. It's supposed the person stays still and thus the face detector is set to execute only for a second. Also, to boost the performance further, only region within the face rectangle is magnified, requiring it to be very still. For achieving this the position and size of face'srectangle is fed into Eulerian video magnification method and interpolated between previous and newly detected faces, if distance between the two, *d*, is less than one third of previous face's rectangle width, *w*. that is .$d<\frac{w}{3}$.

And interpolation percentage, *r* is given by, $r=\frac{3d}{w}$. Face tracking is done by comparing newly detected faces and the ones that are already detected. Any older face which doesn't match with the new ones is marked for deletion. It's deleted only when it fails to match again the next time detector is executed. In case the newly detected faces are equal or more than the older faces, then each older face is matched to the nearest newly detected face, any non-matching newly detected face is marked as a new face.

**Eulerian video magnification**

**Concept**

The video magnification method being used in the system focuses on amplifying color and low-amplitude motion in videos, which are otherwise invisible to naked eyes. The basic approach considers time series of color values at any spatial location and amplify variation in a given temporal frequency band, previous attempts made in this direction used Cartoon Animation Filters[8] based on Langrangian perspective, where the trajectory of particles is tracked over time. Eulerian video magnification is rather inspired by the Eulerian perspective, where properties of a voxel of a fluid, such as pressure and velocity, evolve over time. The approach is the exaggeration of motion by amplifying temporal color changes at fixed positions. This approach reduces the complexity and computation cost of the algorithm. First, the video sequence is decomposed into different spatial frequency bands, which are magnified differently as they have different signal-to-noise ratio[9]. The full laplacian pyramid[10, 11] is calculated and each spatial band undergoes a uniform temporal processing. The extracted band-pass signal is magnified by a factor α, finally magnified signal is added to the original one and the spatial pyramid collapsed as shown in Fig. I.

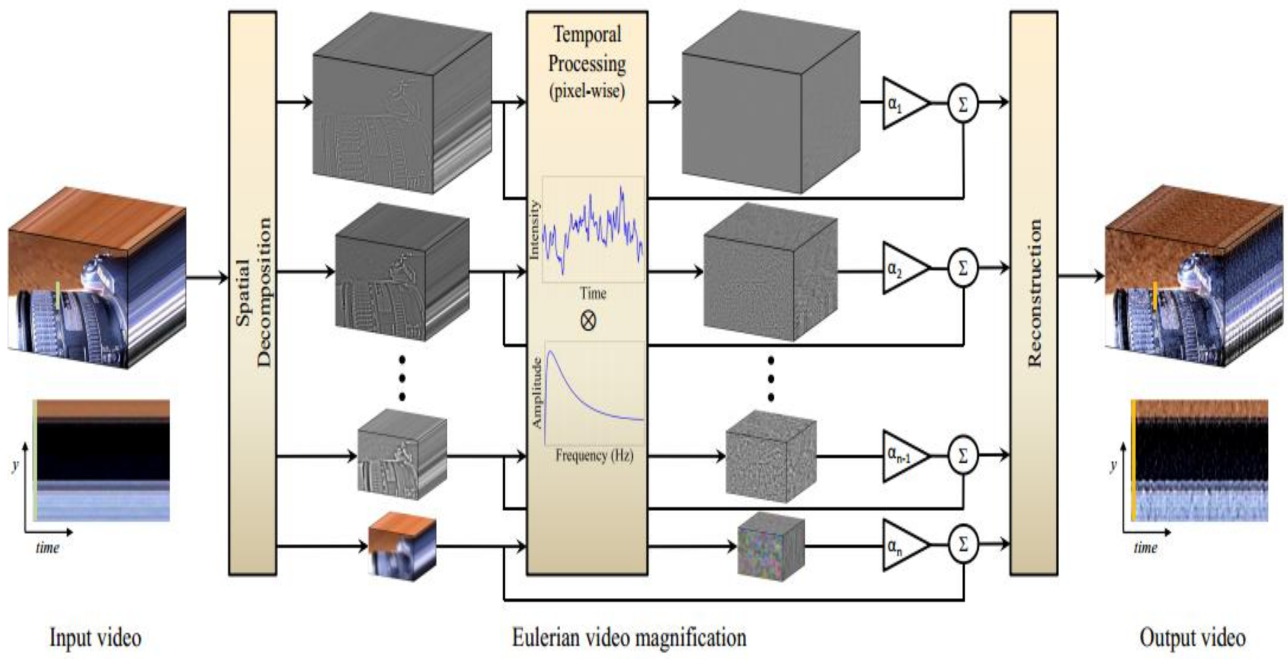


**Figure I: Eulerian Video Magnification.**

Estimation of size of the spatial filter needed to reveal a signal at a certain noise power level gives

$$S(\lambda) = S(r) = \sigma'^2 = k\,(\sigma/r)^2$$

Where$S(\lambda)$ represents signal over spatial frequencies, and since wavelength $\lambda$ is proportional to the radius $r$ the signal is represented as $S(r)$. As the filtered noise power $\sigma'^2$ is inversely proportional to $r^2$ equation can be solved for $r$, where k is constant dependent on filter's shape.

To understand the whole process we consider a simple 1D signal undergoing translational motion, which can then be generalized to 2D motion. Let $I(x,t)$ denote image intensity at position $x$ and time $t$. The observed intensities expressed w.r.t a displacement function $\delta(t)$, such that $I(x,t) = f(x + \delta(t))$ and $I(x, 0) = f(x)$. The goal of motion magnification is synthesis of following signal.

$$I(x,t) = f(x + (1 + \alpha)\,\delta(t)) \qquad (eq.1)$$

For some amplification factor $\alpha$, Approximating image by a first order Taylor series expansion,

$$I(x,t) \approx f(x) + \delta(t)\frac{\delta f(x)}{\delta x} \qquad (eq.2)$$

$B(x, t)$ be broadband temporal band-pass filter to $I(x,t)$ at every $x$ containing motion signal $\delta(t)$

$$B(x, t) = \delta(t)\frac{\delta f(x)}{\delta x} \qquad (eq.3)$$

We then amplify the band-pass signal by $\alpha$ and add it back to original signal. Finally we get,

$$\tilde{I}(x,t) \approx f(x) + (1+\alpha)\,\delta(t)\frac{\delta f(x)}{\delta x}$$

Or simply,

$$\tilde{I}(x,t) \approx f(x + (1+\alpha)\,\delta(t)) \qquad (eq.4)$$

This shows that processing magnifies the motion, the spatial placement $\delta(t)$ of local image $f(x)$ at the time $t$, has been magnified to a magnitude of $(1+\alpha)$. However, in a more general case where $\delta(t)$ is not completely in the pass-band, only specific temporal spectrum components denoted by $\delta_k(t)$ will be attenuated by a temporal filtering factor $\gamma_k$ this temporal frequency dependent attenuation can be interpreted as frequency dependent motion magnification factor $\alpha_k = \gamma_k\alpha$, resulting in a motion magnified output,

$$\tilde{I}(x,t) \approx f(x + \textstyle\sum_k (1+\alpha_k)\delta_k(t)) \quad (eq.5)$$

From further calculations on boundary value for $\alpha$, in terms of spatial wavelength $\lambda = \frac{2\pi}{\omega}$ of the moving signal, yields the largest amplification factor, for accurate motion magnification as follows

$$(1 + \alpha)\delta(t) < \frac{\lambda}{8} \quad (eq.6)$$

The choice of filter is application dependent, for motion magnification a broad pass-band is preferred. For color amplification of blood flow a narrow band-pass or an Ideal band-pass is preferred. A Low-order infinite impulse response filters for both and is convenient for a real IIR with cutoff frequencies $\omega_l$ and $\omega_h$ to construct an infinite impulse response filter band-pass filter. We then select desired magnification factor α and spatial cutoff frequency $\lambda_c$. For amplifying color change due to blood flow through face, a Laplacian pyramid is first applied and α is set for finest of two levels to 0. It is then down-sampled and a spatial low-pass filter is applied to each frame reducing both quantization and noise and for boosting subtle pulse signal which are of interest. Each frame sequence is then passed through an ideal band-pass filter with first frequency of 0.4-4 Hz, corresponding to 24-240 beats per minute (bpm) and then a narrow band of 0.83-1 Hz (50-60 bpm) may be used when extraction is successful. To emphasize color change as much as possible, a large amplification factor, $\alpha = 100$ and spatial cutoff frequency $\lambda_c = 1000$ is applied. An attenuation of $\alpha = 0$ is used for $\lambda_< \lambda_{c.}$

**Implementation**

The final implementation is done in C/C++ to reduce development bottlenecks due to premature stage of OpenCV Java binding, further reducing the JNI calls from Android Java virtual machine and increasing the application performance. A performance optimized EVMGdownIIR filter is used.

Resize Down: A spatial filter is applied after calculating level of Gaussian pyramid. This is done by looping to the desired level; previous loops are fed to next loops. Gaussian pyramid level is calculated by convolving input frame with kernel K:

$$K = \frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

And then, down-sampling the frames by rejecting even rows and columns. However, for better performance instead of iterative resizing, a single resize operation using OpenCV interpolation method named area is used to resize it to a predefined size.

Temporal Filter: It is an infinite impulse response band-pass filter constructed by subtracting two first-order low-pass infinite impulse response filters, where each is computer as follows

$$L_n = L_{n-1} * (1- \omega) +\omega * M$$

Where M is the current frame, L is the low-pass filter accumulator per frame and ω is the cutoff frequency percentage.

Amplification: Here the result of temporal filter is magnified using a factor α resulting in amplified color variations.

Resize up: Here the step of resize down is reversed, by up-sampling the frames by inserting even rows and columns with zeroes, and later convolving the input frame with the same kernel multiplied by 4. For better performance however, a single resize operation based on linear interpolation method is used.

**De-trending**

De-trending[12] is necessary to remove the surplus ultra-low frequency trends from the input signal without distorting the magnitude, thus acting like a high pass filter. The input signal $z$ is converted into a two component signal $z = z_{static} + z_{trend}$, while $z_{static}$ is a nearly stationary component $z_{trend}$ is a low frequency aperiodic trend. Estimation of stationary component gives the following,

$$z_{static} = (I - ( I + \lambda^2 D_2^T D_2)^{-1})\, z$$

Where $I$is the identity matrix, $D_2$ is discrete approximation of second order and $\lambda$ is the regularization parameter. This uses real RR series and its effect on time and frequency[13] domain analysis of heart rate variability is lossless.

**Pulse Rate Estimation**

For converting the extracted photo-plethysmographic signal into the number of beats per minute, following methods are used

**Power Spectrum**

To calculate power spectrum, we multiply the Fourier transform with itself. As here the values are captured from a video, sequence of frames, function of time is discrete with frequency rates equal to video frame rate, Frames per second. The index $i$, corresponds to maximum of power spectrum convertible to frequency value $F$.

$$F = \frac{\mathrm{i} * \mathrm{FPS}}{2\mathrm{N}}$$

Where N is the size of extracted signal. F is multiplied by 60 to obtain beats per minute.

**Pulse Wave Detection[14]**

A simplified description to obtain an estimated heart rate from PPG signal is discussed below. Identification of possible peaks and foots of individual pulses

**Maximum (MAX)**

The signal is divided into consecutive 200ms time intervals and for every segment the absolute maximum is determined.

Ones which fall below a certain threshold are rejected, or if distance between two maximums is less than or equal to 200ms, then lower one is rejected.

**Minimum (MIN)**

The absolute minimum is determined between every two adjacent maximums. One which are more than a certain threshold are rejected. When it is rejected, the lower-amplitude maximum of the two maximum adjacent to the rejected minimum is discarded too.

Examination and verification of the rising edges is done as follows:

If a rising edge is rejected, its maximum and minimum are rejected. A rising edge is rejected when its amplitude (i.e. MAX - MIN) is lower than amplitude threshold; or its duration is lower than a threshold that depends on the sampling rate; or its amplitude doesn't increase smoothly.

Estimation of the similarity, if the amplitude of the lower-amplitude rising edge is greater than 50% of the amplitude of the higher-amplitude rising edge; and if the maximum of the lower-amplitude rising edge is between ±60% of the maximum of the higher-amplitude rising edge; and if the minimum of the lower-amplitude rising edge is between ±60% of the minimum of the higher-amplitude rising edge; and if the duration of shorter rising edge is greater than 33% of the duration of the longer rising edge. The valid rising edges are then categorized according to its characteristics for the following steps.

The present rising edges are verified by categorizing on the previous step, which are considered valid edges of a pulse wave if they fulfill at least one of the decision rules. Description of validation process is necessary to discard signals which are not representative of pulse waves. Providing a way of calculating the heart rate estimation only on valid pulse signals.

**Validating Signal**

It is important to validate the signal and is done in two phases, first raw signal composed of average of the mean values of the green channel of the rectangle's face is checked for noise, after which the on step *validate signal*, the timing and shape of normalized and detrended signal is verified.

If the signals standard deviation is higher than 50% of α, amplification factor thenthe raw signal can be verified. After this, following steps are applied over it:

i. De-trendas described in section 2.3

ii. Normalization, the de-trended signal $S$ is normalized to $S'$ by subtracting the mean of signal i.e. $\hat{S}$ and dividing it by its standard deviation, $\sigma$:

$$S' = \frac{S-\hat{S}}{\sigma}$$

iii. Mean filtering, done by convolving the signal 3 times with the kernel K:

$$K = \frac{1}{5*5}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Finally, the fast pulse wave detection algorithm discussed in section 2.4.2, is used to validate the shape and timing of the signal. Possible signal peaks or absolute maximums are identified by dividing it into consecutive 200*ms* time intervals.

Maximums are only considered valid if they aren't boundary values of the segment, and if they are above the threshold, which is 62% of the amplitude mean of possible identified peaks so far; or in case of less than 200*ms* distance between two maximums, the lower one is rejected. Also to prevent an error due to missed or miscounted peak, the signal is kept valid for next 25 frames. The validation is finalized when:

i. Signal includes at-least two or more maximums or peaks

ii. Peak count falls between valid infant heart beat range, i.e. 24to 240 bpm

iii. Standard deviation of peak's amplitude is less than 0.5

iv. Standard deviation of time interval between peaks is less than 0.5

Also to reduce the error due to miscounting of the peaks which could add up to a large error considering short signal analysis period of 5 sec at 24 frames per second, apart from the pulse wave detection algorithm discussed as above, the values are averaged over values obtained from the power spectrum method every second.

**Result and Discussion**

Test results were run on a population of 74 participants. Averaged means were then calculated over 12 readings for all the participants, the results from the samples are measured from Minder, the application developed against Samsung Galaxy S5's Pulse rate meter sensors.

The subjects pulse was measured in relaxed position, readings shown in Table (a). After this heart beat reading were recorded after physical exercise, giving the results as recorded in Table (b).A plot of the difference between the two readings obtained from above tables is plotted as follows; it can be observed that difference is greater in upper ranges as shown in Fig. II.

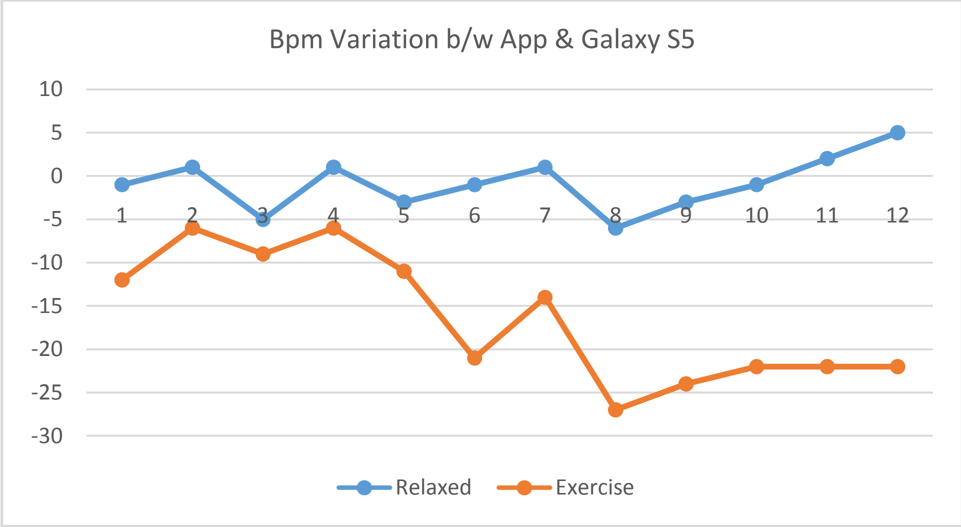


**Figure II: BPM variation graph.**

| Readings | App (bpm) | G S5 (bpm) | Diff. (bpm) |
|---|---|---|---|
| 1 | 49 | 50 | -1 |
| 2 | 52 | 51 | +1 |
| 3 | 51 | 56 | -5 |
| 4 | 61 | 60 | +1 |
| 5 | 48 | 51 | -3 |
| 6 | 51 | 52 | -1 |
| 7 | 53 | 52 | +1 |
| 8 | 49 | 55 | -6 |
| 9 | 61 | 64 | -3 |
| 10 | 63 | 64 | -1 |
| 11 | 66 | 64 | +2 |
| 12 | 55 | 60 | +5 |

**Table (a): Bpm difference between App andGalaxy S5 (Relaxed).**

| Time (sec) | App (bpm) | G S5 (bpm) | Diff. (bpm) |
|---|---|---|---|
| **1** | 69 | 80 | -11 |
| **2** | 72 | 79 | -7 |
| **3** | 71 | 75 | -4 |
| **4** | 68 | 75 | -7 |
| **5** | 78 | 86 | -8 |
| **6** | 61 | 81 | -20 |
| **7** | 83 | 98 | -15 |
| **8** | 69 | 90 | -21 |

| | | | |
|---|---|---|---|
| **9** | 81 | 102 | -21 |
| **10** | 83 | 104 | -21 |
| **11** | 86 | 110 | -24 |
| **12** | 65 | 92 | -27 |

**Table (b): Bpm difference between App andGalaxy S5 (After Exercise).**

While the application is accurate to ±2% for lower heart beat ranges i.e. till 60-65 bpm. Its accuracy is compromised as the heart beat rate rises, the possible reason being the readings lost due to earlier frames being in the processing stage i.e. slower processing rates. However, these results are averaged over 5 minutes for every participants, the individual differences between each reading is considerably low most of the times. Nevertheless, the system requires further work before it can be approved as medically trustworthy and optimization is required to improve its accuracy in the upper range of pulse rates. The initial results obtained may not be accurate, but with further optimizations and improvements better results can be expected. The application itself has many possible extensions, e.g. keeping a history of each and every patient and processing all the data through an online system. Patterns of various disorders can be identified and used to further improve the results of the system. Thus, user can be made aware of an eminent heart attack, blockage and early stage respiratory disorders by the application, giving them more time to act.

## Conclusion

Mobile version of heart rate monitor, based on Eulerian video magnification proved accurate for the lower range of heart beats, although the variation in reading was more in the higher regions. It can successfully monitor human, but further tests and optimizations are needed to make it more accurate or use it as an alternate to medical diagnostic devices. It can provide a cost-efficient and viable alternative to costly and bulky monitoring systems, proving an easy and efficient mobile diagnostic system. As processing power of mobile devices is increasing at a fast pace, systems like Minder and other mobile based health diagnostic systems will make lives of people much healthier and healthcare more affordable in developed as well as developing countries. Future work includes respiration rate monitoring and blood oxygen monitoring, which will make it a standalone all vital monitoring system for infants and neo-natal, prone to or suffering from respiratory or cardiovascular disorders.

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