References

EVM and PPG Technologies:

• Eulerian Video Magnification (EVM) is a remarkable technique that can be used to measure physiological parameters such as heartbeat, Heart Rate Variability (HRV), and stress from webcam video recordings. EVM enhances subtle color and motion variations in video frames, making it possible to visualize physiological signals that are typically imperceptible to the naked eye. Here's a detailed explanation of how EVM works for these measurements, along with the technological stack and machine learning algorithms often used:

Eulerian Video Magnification for Heartbeat Measurement:

- 1. **Color Magnification**: EVM starts by decomposing the video into different frequency bands using a spatial decomposition. Each band represents a different scale of motion and color variation. The technique then magnifies specific frequency components associated with physiological signals, like the pulse-induced color changes in the skin.
- 2. **Heartbeat Extraction:** By focusing on the amplified color variations in the skin region, EVM allows for the extraction of pulse signals. The algorithm identifies changes in skin color corresponding to the heartbeat cycle, typically in the form of rhythmic intensity variations.
- 3. **Heart Rate Calculation**: Once the pulse signal is extracted, the next step is to calculate the heart rate. This is done by measuring the time interval between successive peaks or troughs in the pulse signal, giving the heart rate in beats per minute (BPM).

Eulerian Video Magnification for HRV Measurement:

- 1. **Temporal Analysis**: HRV is the variation in time between successive heartbeats. EVM can capture HRV by analyzing the time intervals between the peaks (R-waves) of the electrocardiogram (ECG) signal, which is typically synchronized with the video recording.
- 2. **Frequency Domain Analysis**: EVM can also be used to perform a spectral analysis of the heart rate signal to determine the frequency components associated with HRV, such as the high-frequency (HF) and low-frequency (LF) components.

Eulerian Video Magnification for Stress Assessment:

- 1. **Stress-Related Color Changes**: Stress can lead to changes in blood flow and skin color, which are often subtle but can be detected using EVM. EVM can amplify these color changes and make them more visible in the video frames.
- 2. **Machine Learning Algorithms**: To assess stress levels accurately, machine learning algorithms can be trained to analyze the amplified video data. These algorithms can recognize patterns in color variations, facial expressions, and other visual cues associated with stress.

Technological Stack:

The technological stack for implementing EVM for physiological measurements using a webcam typically includes:

OpenCV: An open-source computer vision library that provides tools for video processing and image analysis.

Python: A programming language commonly used for scientific computing and machine learning.

Machine Learning Frameworks: Libraries like TensorFlow, PyTorch, or scikit-learn can be used to develop and deploy machine learning models for stress assessment.

Webcam: A standard webcam is used to capture video footage.

Machine Learning Algorithms:

For stress assessment, various machine learning algorithms can be employed, including:

Convolutional Neural Networks (CNNs): These deep learning models can extract features from video frames and recognize patterns associated with stress.

Support Vector Machines (SVM): SVMs can classify stress based on features extracted from the video data.

Recurrent Neural Networks (RNNs): RNNs can model temporal dependencies in the data, which is crucial for HRV analysis.

The choice of algorithm depends on the specific requirements of the stress assessment task and the available data.

In summary, Eulerian Video Magnification, when combined with machine learning algorithms, offers a non-invasive and innovative way to measure physiological parameters such as heartbeat, HRV, and stress using a webcam and video recordings. The technology stack includes open-source tools like OpenCV and Python, while machine learning algorithms provide the capability to analyze the amplified video data for accurate physiological measurements and stress assessment.

 Photoplethysmography (PPG) is a non-invasive optical technique that can be used to estimate blood pressure (BP) using a webcam. It measures changes in blood volume in the microvascular tissue bed of the skin, typically the fingertip. Here's a detailed explanation of how PPG can be used for estimating BP, along with the technological stack and potential machine learning algorithms involved:

PPG for Blood Pressure Estimation:

- 1. **Light Absorption and Reflection**: PPG involves illuminating the skin with a light source, often an LED, and then measuring the amount of light absorbed and reflected by the blood vessels. Blood absorbs more light than surrounding tissues, and the amount of absorption varies with changes in blood volume, such as those associated with the cardiac cycle.
- 2. **Photodetector:** A photodetector, such as a photodiode or phototransistor, captures the light that has passed through the skin. The detected light intensity is converted into an electrical signal.
- 3. **Signal Processing**: The PPG signal obtained from the photodetector typically consists of a pulsatile component (related to the cardiac cycle) and a non-pulsatile component. The pulsatile component contains information about the heart rate, pulse wave, and can be used to estimate BP.
- 4. **Feature Extraction**: Various features can be extracted from the PPG signal, such as the amplitude of the pulsatile component, the time between specific points in the waveform (e.g., the time between the R-peak of the ECG and a specific point in the PPG waveform), and the shape of the waveform.
- 5. **BP Estimation Models**: Machine learning models can be trained using PPG features and reference BP measurements (e.g., cuff-based BP measurements). These models can establish a relationship between the PPG signal characteristics and BP levels.

Technological Stack:

The technological stack for implementing PPG-based BP estimation using a webcam typically includes:

OpenCV: An open-source computer vision library that provides tools for video processing and image analysis.

Python: A programming language commonly used for scientific computing and machine learning.

Machine Learning Frameworks: Libraries like TensorFlow, PyTorch, or scikit-learn can be used to develop and deploy machine learning models for BP estimation.

Webcam: A standard webcam is used to capture video footage of the fingertip or another suitable location.

Machine Learning Algorithms:

For BP estimation, machine learning algorithms can be employed, including:

Regression Models: Linear regression, support vector regression (SVR), or more complex regression models can be used to predict systolic and diastolic BP based on PPG features.

Deep Learning Models: Convolutional neural networks (CNNs) or recurrent neural networks (RNNs) can be employed to automatically extract features from PPG signals and estimate BP levels.

Formulas:

The exact formulas used for BP estimation would depend on the specific machine learning model and features selected. Generally, regression-based models would use linear or non-linear equations to relate PPG features to BP levels.

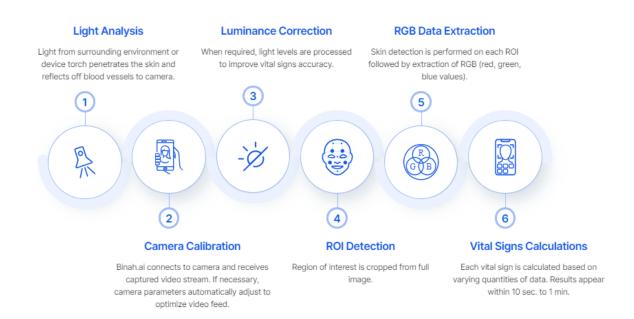
For instance, a simplified linear regression formula for estimating systolic BP might look like:

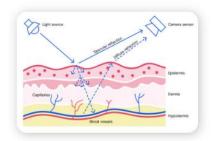
Systolic BP = a * PPG_feature1 + b * PPG_feature2 + c

Here, 'a,' 'b,' and 'c' are coefficients learned during the model training process.

In summary, PPG-based BP estimation using a webcam involves capturing and analyzing optical signals from the fingertip. Machine learning algorithms are used to relate PPG features to BP levels. The technological stack includes open-source tools like OpenCV and Python, along with machine learning frameworks for model development. Specific formulas would depend on the chosen machine learning model and features.

How Our Technology Works







Contactless Video-based rPPG

For contactless data extraction, Binah.ai uses rPPG (remote photoplethysmographic imaging). rPPG is a camera-based solution for contactless cardiovascular monitoring, proven to be as accurate as traditional PPG devices. Our technology measures the changes in red, green, and blue light reflected from the skin and quantifies the contrast between specular reflection and diffused reflection.

Contact-based PPG

For challenging conditions, Binah.ai has implemented a backup contact-based solution. The contact-based solution extracts a PPG signal when users place a finger on the rear camera of a smartphone. Binah.ai automatically detects when conditions are not ideal for contactless rPPG extraction and suggests using the contact-based extraction.

Abnormal measurement results can be related to the following health issues and may require attention:

| Parameter | | | | Normal Range (Age 18+) | | Health Issues Associated with Abnormal Levels | | | |
|---|---|-----|---|---------------------------------------|---|---|--|---|-----|
| Blood pressure The pressure of circulating blood against artery walls | | | | Systolic: < 120 Diastolic: < 80 | | Heart attack, heart disease, stroke, kidney disease, poo cognitive function, dementia | | | |
| Heart Rate / Pulse Rate The number of times a person's heart beats per minute | | | | 60-100 bpm | | Stroke, heart failure | | | |
| Heart Rate Variability The variance in time between heart beats | | | | Age 20-25: 55-105 Age 60-65: 25-45 | | Stress, risk of cardiac events, oncoming sickness, nutrition and sleep patterns | | | |
| Oxygen Saturation The amount of oxygen-carrying hemoglobin in the blood relative to the amount of hemoglobin not carrying oxygen | | | | 95% – 100% | | Heart disease, interstitial lung disease, COPD, anemia, ARDS, pneumonia, sleep apnea | | | |
| Breathing Rate The number of breaths a person takes per minute | | | | 12-20 bpm | | Anxiety, fever, heart problems, respiratory conditions including, COPD, asthma, and pneumonia | | | |
| Pulse Respiratory Quotient (PRQ) Heart rate divided by respiration rate, captures the complex state of cardiorespiratory interactions | | | | 5 | | Hyperventi | Hyperventilation, cardiorespiratory issues | | |
| | | Low | | | | | | | Hig |
| | | | | | | | | | |
| 4 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |

Medium

Vital Parameters:

• Heart Rate / Pulse Rate : <u>Click Here</u>

• Heart Rate Variability : <u>Click Here</u>

• Stress Detection : <u>Click Here</u>

• Blood Pressure Monitoring: <u>Click Here</u>

• Respiration Rate : <u>Click Here</u>