The Way SmartWatches Work

Step counting, heart rate, and burned calories measurement

Fatemeh Rashidi

University of Tehran - Computer Science Department

February 2024

Contents

1. Key considerations in the design of wearable PPG[1] devices
2. The physiological parameters that can be estimated from wearable PPG signals
3. Potential applications in health and fitness monitoring, measuring mechanism of health track devices

1. photoplethysmogram

1

Key considerations in the design of wearable PPG devices

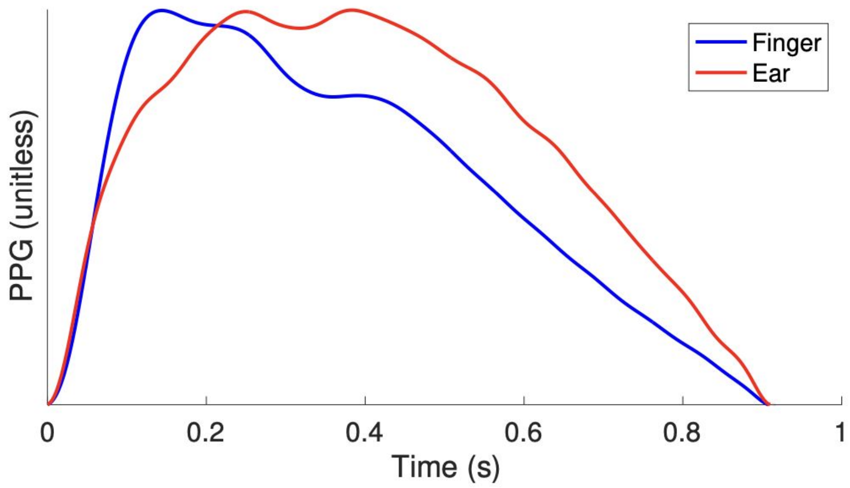
1. Measurement site
2. Sensor design

1. Measurement site

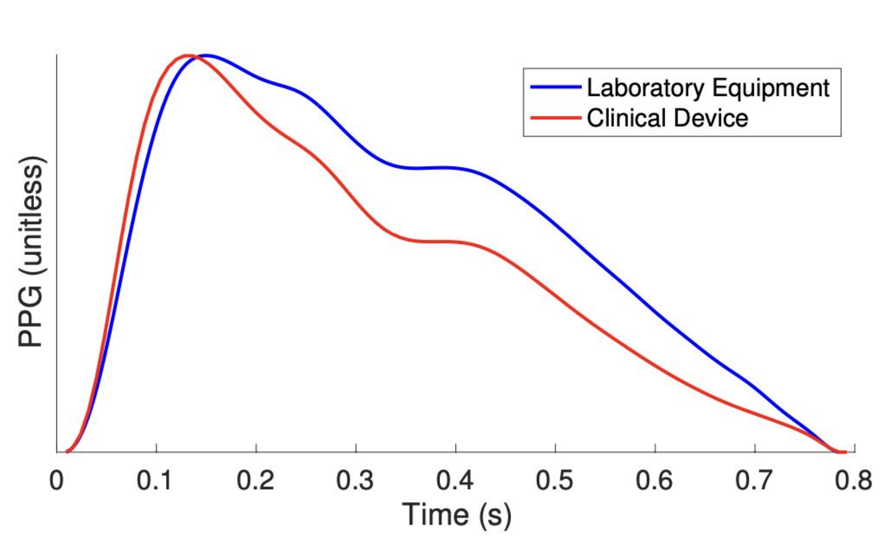
- Utility of the acquired PPG signals
  - The PAT[2] is greater at sites further from the heart such as fingers or toes.
- User acceptability of the wearable device

2. pulse arrival time-the time delay between ventricular contraction and PPG pulse wave arrival

- Finger
  - Placed on the underside of the finger in order to obtain a reflectance PPG signal from as close as possible to the main arteries in the finger
  - Oximeters
- Wrist
  - acquires reflectance signals at the upper wrist
  - much higher signal-to-noise ratios
  - accurate HR measurements
- Ear
  - Less likely to be affected by motion artifacts
- Chest
  - Ideal location for acquiring electrocardiogram and seismocardiogram signal
- Face
  - acquire PPG signals at either the nose bridge or the temple
  - more accurate than other sites



Different wave shapes are acquired from finger and ear



Different wave shapes are acquired using different devices

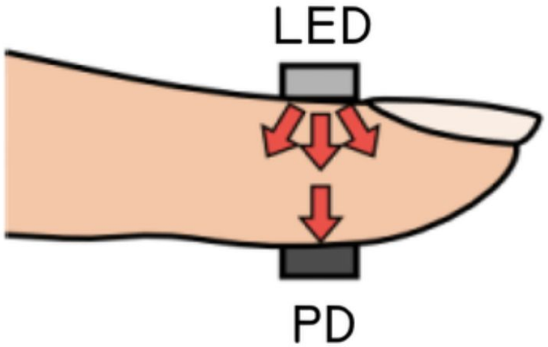
2. Sensor design

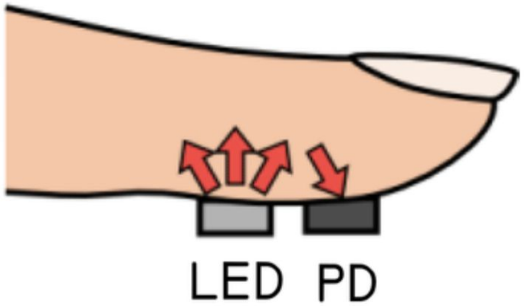
- **Transmission photoplethysmography**
  (Measuring through the body)

  Can be used at limited sites such as the finger, toe or earlobe.

- **Reflectance photoplethysmography**
  (Measuring from the skin's surface)

  Superior signal-to-noise ratio
  → More suitable for use in wearable devices





PPG wavelength

Infrared/ Red

- Longer wavelength
- Used for transmission photoplethysmography(PPG)

Green

- Higher signal-to-noise ratio
- Less affected by changes in temperature

Use both green and red lights:
Green, during exercise
Infrared/red, rest time

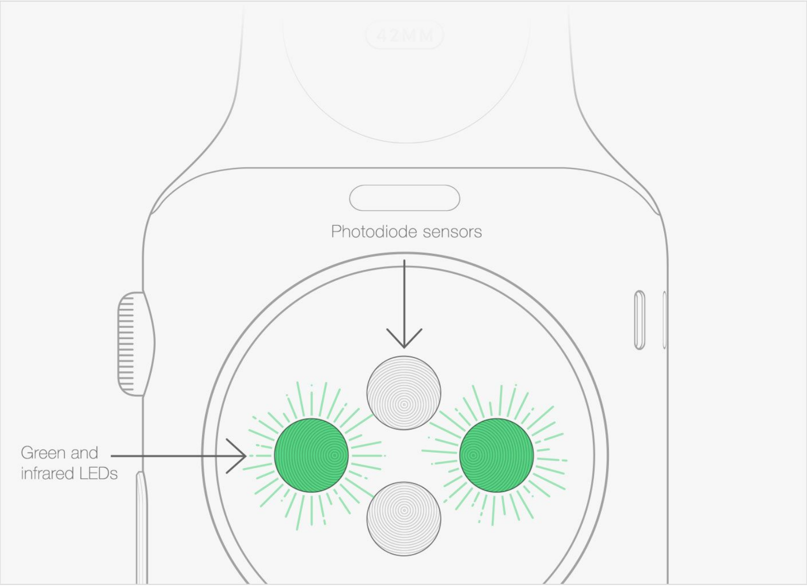
2

The physiological parameters that can be estimated from wearable PPG signals

Heart Rate(HR)

- Band-pass filtering
  - Filter signal to focus on a specific frequency range and eliminate irrelevant frequency content
- Motion artifact removal
  - Remove movement disturbances
- Initial HR estimate
  - Obtain initial HR estimation by analysing the frequency spectrum of the processed PPG signal
- Tracking algorithm
  - Continuously monitor and adjust the HR estimates over time

As blood is red, it reflects red light and absorbs green light. So when your heart beats, there’s more blood flow in your wrist, and more green light absorption. Between heart beats, there’s less absorption of green light.



Arterial Oxygen saturation

Can be estimated from two simultaneous PPG signals of different wavelengths

- Identify individual pulse waves in the two PPG signals
- Calculate the normalised AC component for each signal (defined as the total intensity of light at the systolic peak divided by the total intensity at the pulse onset).
- Calculate the ratio of the normalised AC components for each signal.
- Estimate SpO2 from an empirical relationship between SpO2 and the ratio of normalised AC components

3

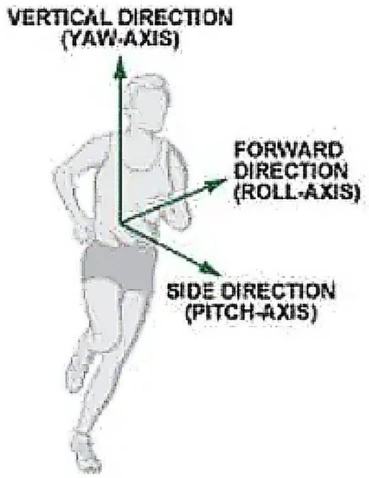
Potential applications in health and fitness monitoring

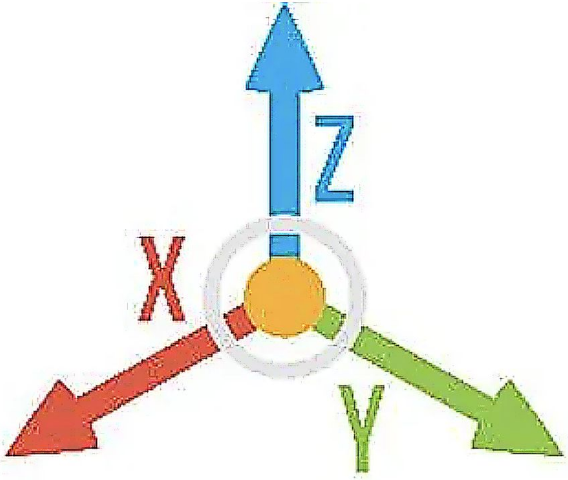
- Heart Rate monitoring
- Step counter
- Sleep tracking
- Blood pressure monitoring
- Blood Oxygen monitoring
- Calories measurement

Pedometer
(Step counter)

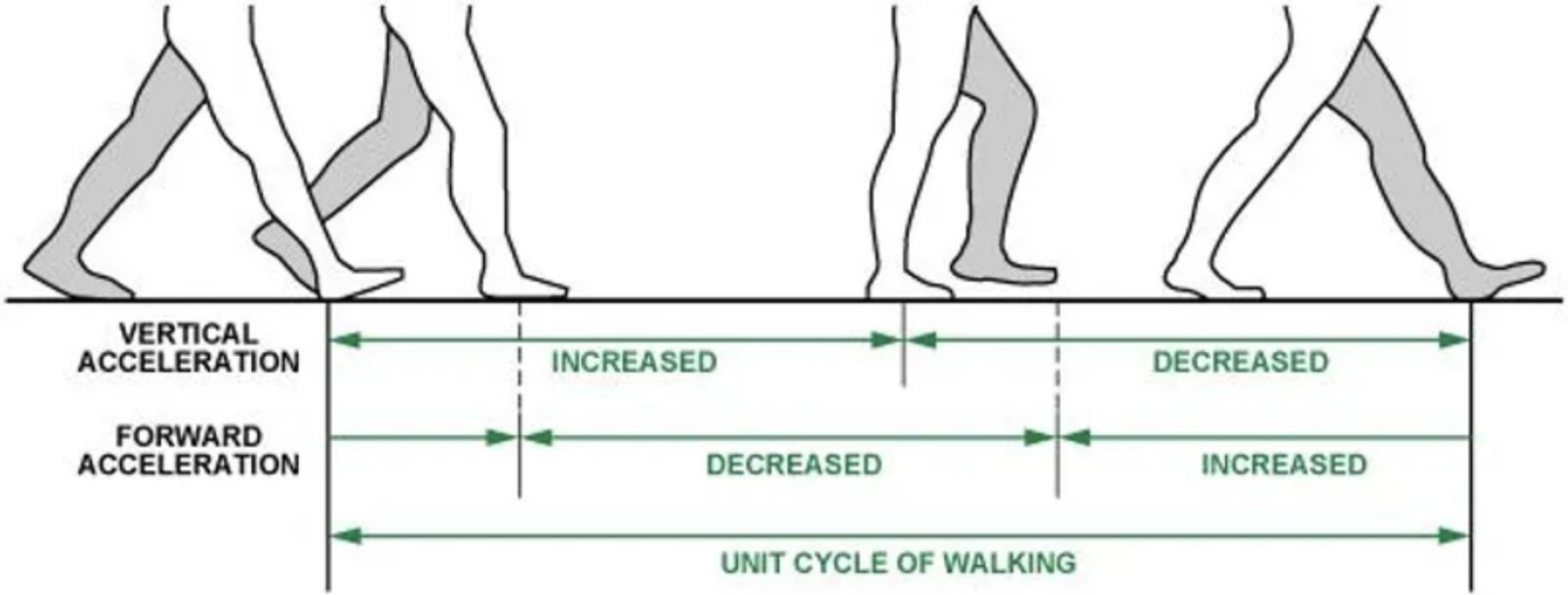
3 Axis Accelerometer(+ motion sensors (Gyroscope))

- Measure triaxial acceleration using MEMS[3]

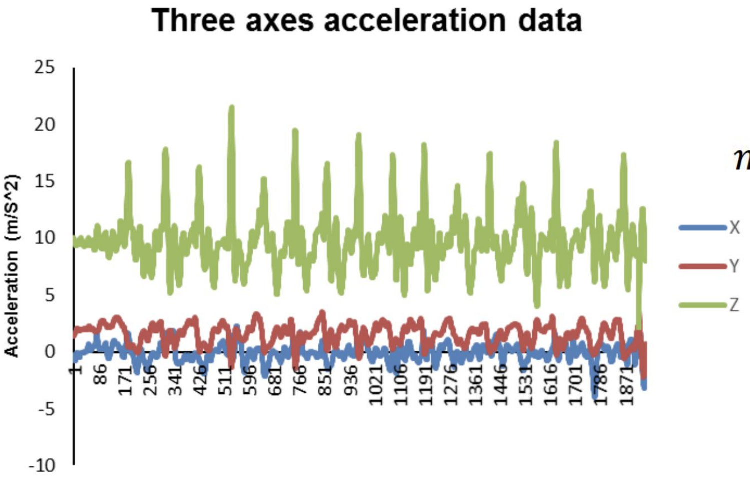




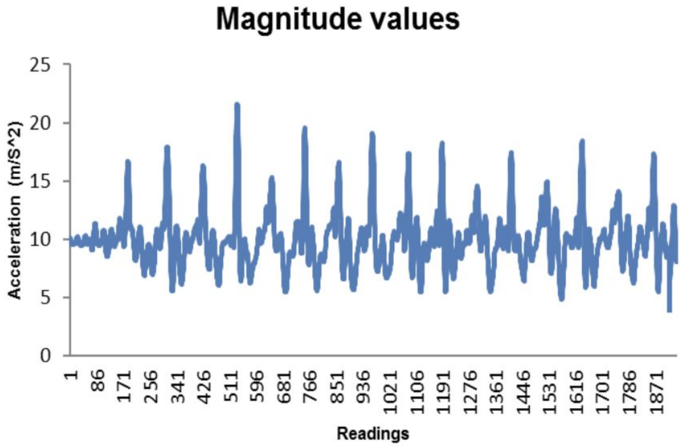
3. microelectromechanical systems



- At least one axis has relatively large periodic acceleration changes.
- Peak detection and a dynamic threshold-decision algorithm for acceleration on all three axis are essential for detecting a unit cycle of walking or running.



$$mag = \sqrt{x^2 + y^2 + z^2}$$



Next step: <u>Digital low pass filtering</u> which causes smoother data.(Kalman, Chebyshev, Butterworth filter)

- Sampling in some fixed intervals(e.g. 100 samples)
- Find maximum and minimum acceleration in the intervals
- Compute dynamic threshold(resulting average)
- Apply dynamic threshold to the next 100 samples
- Count a step if the acceleration drops below the average level

For more accuracy:

Dynamic precision: How fast the acceleration is changing and decides if it's a proper step or just a random movement.

Software logic

1. Calibration
2. Data collection(X, Y, Z axis)
3. Dynamic threshold calculation
4. Sample counter check
5. Step counting

```
calibrate_accelerometer()
{
    for (int i = 0; i < 100; i++) {
        xval[i] = float(analogRead(xpin) - 345);
        sumx = xval[i] + sumx;
        yval[j] = float(analogRead(ypin) - 346);
        sumy = yval[i] + sumy;
        zval[j] = float(analogRead(zpin) - 416);
        sumz = zval[i] + sumz;
    }
    xavg = sumx / 100.0;
    yavg = sumy / 100.0;
    zavg = sumz / 100.0;
}
```

Sample calibration code for MEMS sensor like ADXL335

Sensitivity:

Vibrates very rapidly or very slowly from a cause other than walking or running.

Solution:

Time window and count regulation.

Time window

People can run as rapidly as five steps per second and walk as slowly as one step every two seconds.

0.2s to 2s

Calories Measurement

- Accelerometer
- Heart rate monitor

The faster your heart rate, the more calories you burn.

Physical activity → Accelerated pulse → Burn calories

Calculate burned calories per minute during exercise

Using HR[4], W[6],, and A[7],(based on gender)

```
def calculate_calories_per_minute_men(HR, W, A):
    return (-55.0969 + (0.6309 * HR) + (0.1988 * W) + (0.2017 * A)) / 4.184

def calculate_calories_per_minute_women(HR, W, A):
    return (-20.4022 + (0.4472 * HR) - (0.1263 * W) + (0.074 * A)) / 4.184
```

Using HR, VO_2max, W, and A(based on gender)

```
def calculate_calories_per_minute_with_VO2max_men(HR, VO2max, W, A):
    return (-95.7735 + (0.634 * HR) + (0.404 * VO2max) + (0.394 * W) + (0.271 * A)) / 4.184

def calculate_calories_per_minute_with_VO2max_women(HR, VO2max, W, A):
    return (-59.3954 + (0.45 * HR) + (0.380 * VO2max) + (0.103 * W) + (0.274 * A)) / 4.184
```

Note:

The formula can only be used if the heart rate is **between 90 and 150** bpm.

4. Heart rate
5. Maximum rate of Oxygen consumption
6. Weight
7. Age

Heart Rate	Burned Calories for 65 Kg Female	Burned Calories for 75 Kg Male
90 bpm	199	325
100 bpm	263	415
110 bpm	327	506
120 bpm	391	596
130 bpm	455	687
140 bpm	519	777
150 bpm	583	868

References

1. Peter H. Charlton, Vaidotas Marozas. Wearable Photoplethysmography Devices. the Department of Public Health and Primary Care, University of Cambridge, he Research Centre for Biomedical Engineering, City, University of London, the Biomedical Engineering Institute, Kaunas University of Technology, Kaunas, Lithuania, the Faculty of Electrical and Electronics Engineering, Kaunas University of Technology, Kaunas, Lithuania.
2. Ahmad Abadleh, Eshraq Al-Hawari, Esra'a Alkafaween, Hamad Al-Sawalqah. Step Detection Algorithm For Accurate Distance Estimation Using Dynamic Step Length. IT Department, Mutah University, Mutah, Karak, Jordan, Computer Information, Systems Department, The University of Jordan.
3. Dario Salvi, L. Tarassenko, Carmelo Velardo. An Optimised Algorithm for Accurate Steps Counting From Smart-Phone Accelerometry. Malmö University, University of Oxford.
4. Subir Biswas. How Does A Smart Watch Count Steps | Tech-Knowledge. May 2, 2021.
5. Lara Dugas, Timothy D Noakes, Julia H. Goedecke, Raija Laukkanen. Prediction of energy expenditure from heart rate monitoring during submaximal exercise. Loyola University Chicago, Cape, Peninsula University of Technology, South African Medical Research Council, Polar Electro Europe AG.
6. Subir Biswas. How do Smartwatches Measure Calories | Tech-Knowledge. Jan 3, 2022.

Thanks For Your Attention