The Way SmartWatches Work

Step counting, heart rate, and burned calories measurement

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1 Abstract

In our increasingly digital daily lives, smart devices intensely impact our priorities. One crucial aspect of these devices is their ability to conveniently monitor our well-being. This project explores the world of wearables, such as smartwatches and fitness bands, with a focus on photoplethysmogram (PPG) monitoring.

Key topics covered include the design considerations for wearable PPG-based devices, the physiological parameters derivable from PPG signals, and the diverse applications in health and fitness monitoring. We investigate the mechanisms behind these devices by examining the roles of specific sensors they incorporate.

Today, smartwatches can track various parameters, ranging from heart rate and blood pressure to sleep quality and activities. Additionally, a wide variety of machine learning algorithms is employed in signal processing, filtering, and detection. Consequently, the study of wearable devices is significant since they can conveniently monitor our health and simplify our lives.

2 Introduction

The study of human body health has a long history. In the past, it was conducted by professionals such as doctors. However, in today's world where smart devices are widespread, scientists have opted to measure health using technology due to its continuous and faster nature, as well as its constant accessibility. Thus, smartwatches have emerged.

These days, smart devices play a significant role in our daily lives. People spend a considerable amount of time using these devices, sometimes at the expense of other priorities, particularly their well-being. The potential to monitor body health through this technology causes a significant evolution in our daily routines. The good news is that today, some smart devices function as portable doctors, capable of alerting us to potential risks. Consequently, the study of these devices will ensure the community health.

Wearables such as fitness bands and smartwatches routinely monitor the photoplethysmogram(PPG) signal, an optical measure of the arterial pulse wave which is strongly influenced by the heart and blood vessels. This project presents a comprehensive overview of the state-of-the-art of wearable PPG devices.

We will discuss about:

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

Wearable devices measure physiological parameters using special sensors that are attached to various parts of the human body. In fact, these sensors are affixed to different sites based on their application, and they possess distinct architectures.

These days, smartwatches have the capability to track a diverse range of parameters, including heart rate, blood pressure, blood sugar, blood oxygen, calories burned, sleep quality, electrocardiogram, number of steps, activities, and more.

Moreover, various machine learning algorithms are employed for preprocessing, filtering the acquired signals, scoring, detection, and post-processing. These algorithms operate based on formulas derived from the scientists' research. So, these smart gadgets and nifty algorithms are like our personal health buddies, making it easier to keep an eye on our well-being.

3 Methodology

3.1 Hardware Configurations for Wearable PPG Devices

Wearable PPG[1] devices are now available in a wide range of hardware configurations. In this section, we want to discuss some important factors in hardware design. Since the hardware configuration can influence the utility of the obtained PPG signal for measuring physiological parameters, we need to consider these factors based on the specific application.

[1] photoplethysmogram

3.1.1 Measurement site

Wearable PPG devices can acquire PPG signals from various anatomical sites. The utility of the obtained PPG signals and user acceptability of these devices are influenced by the chosen measurement site. As the site changes, the shape of signals also changes (Fig.1 (a)), potentially affecting the hardware architecture and functionality of the wearable. At sites like fingers or toes, which are farther from the heart, the pulse arrival time[2] (PAT) is greater. Additionally, the design of devices naturally differs based on the measurement site they are intended for. Examples of different devices include wristbands, armbands, earbuds, and glasses.

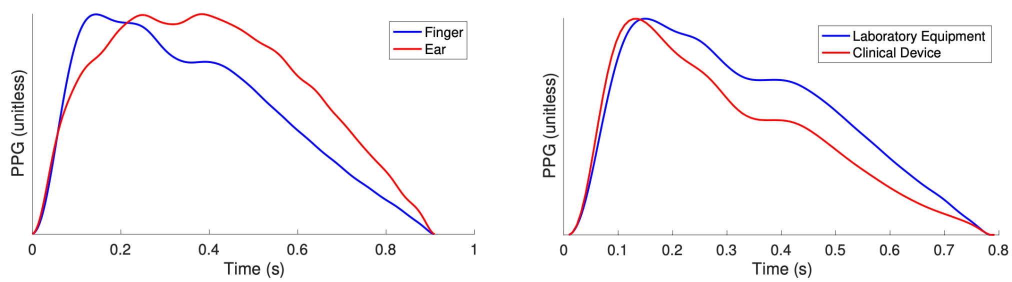

Figure 1: **(a)** Pulse waves at different measurement sites, **(b)** Pulse waves acquired using different devices

The following measurment sites are suitable for wearable PPG signal devices:

1. **Finger**: Smart rings and oximeters are examples of wearable health trackers that are attached to the fingers. The PPG sensor can be positioned underneath the finger to capture a reflective PPG signal from the main arteries in the finger.

2. **Wrist**: Fitness bands and smartwatches acquire PPG signals at the wrist. These devices are typically worn on the upper wrist and can provide accurate HR[3] measurments.

3. **Ear**: Earrings and earbuds are used in the auricular site. As the ear is less likely to be affected by movement, signals obtained from this site are more accurate and encounter fewer noises.

4. **Chest**: Some devices are worn on the chest using a chestband to acquire signals like electrocardiogram and seismocardiogram, which reflect heart activity.

5. **Face**:Noise bridge and temple are sites where facial devices could be worn. Using PPG signal monitors at the temple results in more accurate HR monitoring during exercise.[**1**]

3.1.2 Sensor design

The most crucial component of a health tracker is its sensors. Therefore, studying the hardware architecture of wearable devices to improve measurement accuracy is essential. As it is shown in Fig. 1, pulse waves vary when using different devices, indicating that the hardware configuration could influence parameters extracted from the pulse wave shape.

There are two types of sensors used in health trackers:

1. **Transmission photoplethysmography**: In transmission photoplethysmography, we shine light on a measurment site. Then, we measure how much of that light passes through the body part using a special detector on the other side. However, we can only use this method in specific places where we can put the detector opposite the light source, like the finger, toe, or earlobe.

2. **Reflectance photoplethysmography**: In this type of sensor, we shine light on the skin and measure the light reflected back using a detector near the light source. This approach can be used on various sites like the wrist, arm, or chest. Research has shown that reflectance photoplethysmography provides a more

[2]the time delay between ventricular contraction and PPG pulse wave arrival
[3]Heart Rate

accurate signal at the fingertip compared to transmission photoplethysmography. Therefore, these days, using the reflectance mode is more common.

Another component in wearable devices is the lighting system. These devices often utilize infrared, red, and green lights. Red and infrared lights have longer wavelengths. Consequently, they can penetrate more deeply into the body. On the other hand, since green light has a shorter wavelength, it penetrates less deeply. Therefore, longer-wavelength lights are typically used for transmission photoplethysmography. In contrast, it has been observed that green light has a higher signal-to-noise ratio than red or infrared light in reflectance photoplethysmography.(Fig. 2)

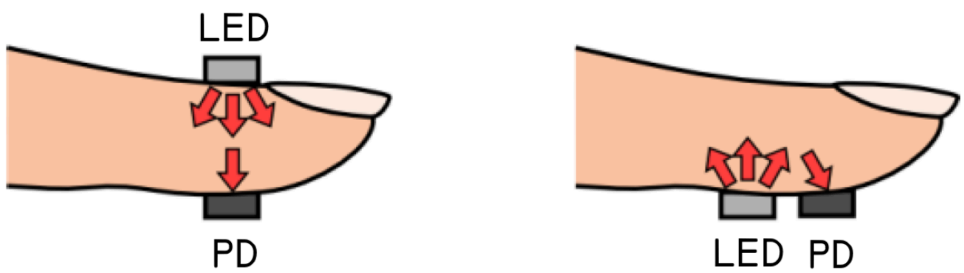

Figure 2: Transmission and reflection PPG working principle.

It is worth mentioning that recent designs capture multiple PPG signals at a single measurment site. This reduces noise and yields more accurate results. Various methods, such as selecting the best signal or combining signals based on quality, are employed for noise reduction. PPG signals of different colors can gather information about various blood vessels. Additionally, using the infrared signal as a motion reference may help counteract the effects of body movement, enhancing the accuracy of green PPG signals.[**1**, **8**]

3.2 The physiological parameters that can be estimated from wearable PPG signals

Several physioligical parameters are estimated by PPG signal devices. The most common and crucial parameter is heart rate, as many other measurements like blood pressure, blood oxygen, and fitness tracking rely on it.

3.2.1 Heart Rate(HR)

The heart produces pulse waves as it pumps. While light is shone on the site, the blood absorbs it. However, as blood is red, it reflects red light and absorbs green. So, after the heart beats, there is more blood flow in the wrist, and more green light is absorbed. Obviously, between heartbeats, the absorption of green light decreases. This change in light absorption leads to HR measurement. More precisely, wearables acquire PPG signals in four steps[**1**]:

1. **Band-pass filtering**: Remove any frequencies that are not within the expected range of heart rates.
2. **Motion artifact removal**: Any motion artifact, such as unwanted movements or disruptions in PPG signals, is removed by using accelerometry signals.
3. **Initial HR estimate**: Obtain initial HR estimation by analysing the frequency spectrum of the processed PPG signal.
4. **Tracking algorithm**: Continuously monitor and adjust the HR estimates over time and eliminate erroneous HRs.

3.2.2 Arterial Oxygen saturation(SpO_2)

Arterial blood oxygen saturation is the proportion of haemoglobin in the blood which is carrying oxygen. SpO_2 can be estimated from two simultaneous PPG signals of different wavelengths as follows[**1**]:

1. **Identify individual pulse waves**: Separate and identify the pulse waves in the two PPG signals.
2. **Calculate normalized AC component**: For each signal, calculate the normalized AC [4] component. This is defined as the total intensity of light at the systolic peak[5] divided by the total intensity at the pulse onset.
3. **Calculate the ratio of normalized AC components**: Find the ratio between the normalized AC components for each signal.
4. **Estimate SpO_2**: Use an empirical relationship between SpO_2 and the ratio of normalized AC components to estimate it.

3.3 Potential applications in health and fitness monitoring

Wearable devices track various parameters such as heart rate, blood pressure, blood oxygen levels, and calories burned. Additionally, they can measure activities such as walking, sleeping, and exercising.

3.3.1 Pedometer (Step counter)

Pedometers work based on MEMS[6] sensors and suitable software to detect steps efficiently. This device measures acceleration in three axes primarily (Fig. 3). However, there are updated versions of pedometers that use motion sensors (gyroscope) for more accuracy.

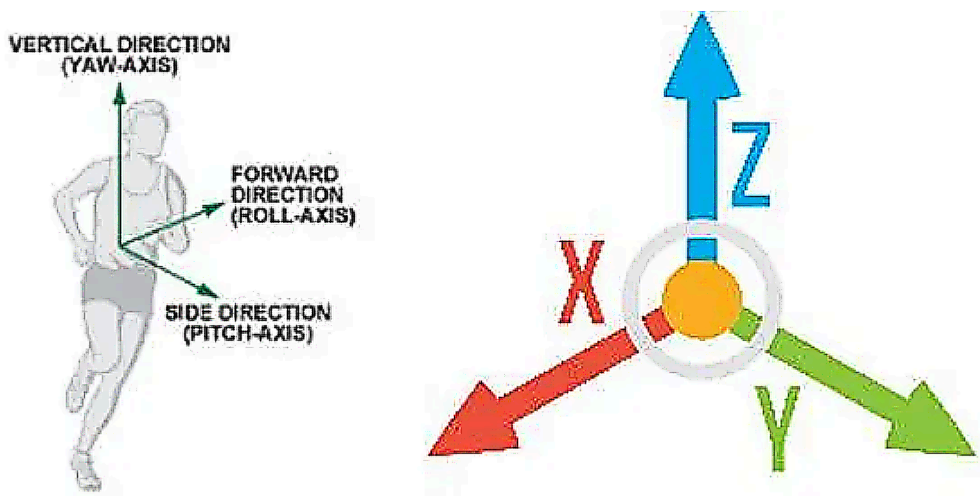

Figure 3: triaxial acceleration

Obviously, at least one axis will exhibit relatively large periodic acceleration changes (Fig. 4). This indicates that during walking or any other physical activity, acceleration changes, and these changes play a significant role in detection. An important task in this area is peak detection. Thus, we have to set a threshold using a dynamic threshold-decision algorithm for acceleration on all three axes to detect a walking cycle.

[4] alternating current
[5] highest point during contraction of the heart
[6] microelectromechanical systems

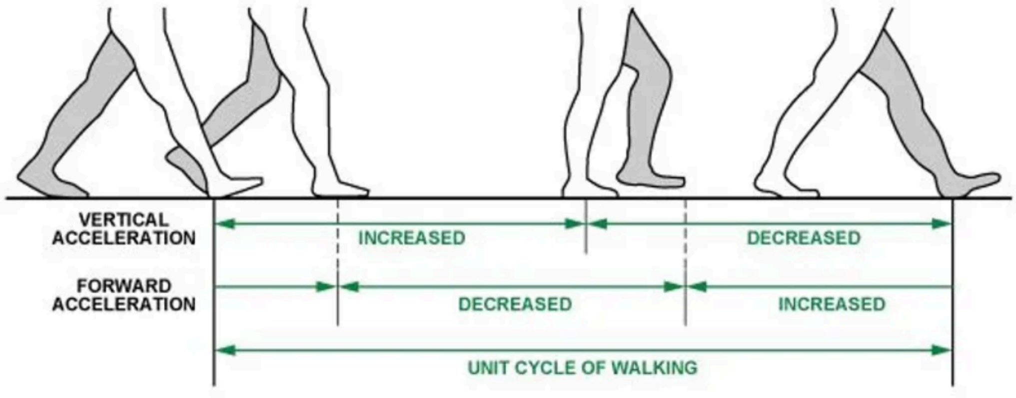

Figure 4: Unit cycle of walking

Fig. 5 shows x, y and z acceleration measurements corresponding to vertical, forward, and side acceleration of a running person. as there are different parameters, we have to combine these values by computing the magnitude value using the following formula:

$$mag = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

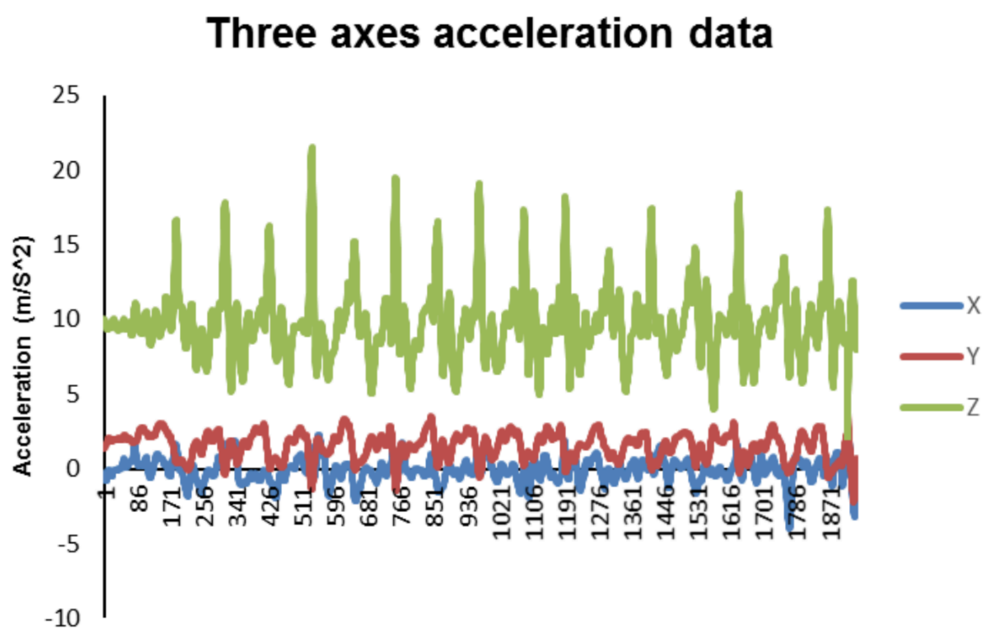

Figure 5: Acceleration on three axes

the result of applying Eq. 1 is shown in Fig. 6.[**2**]

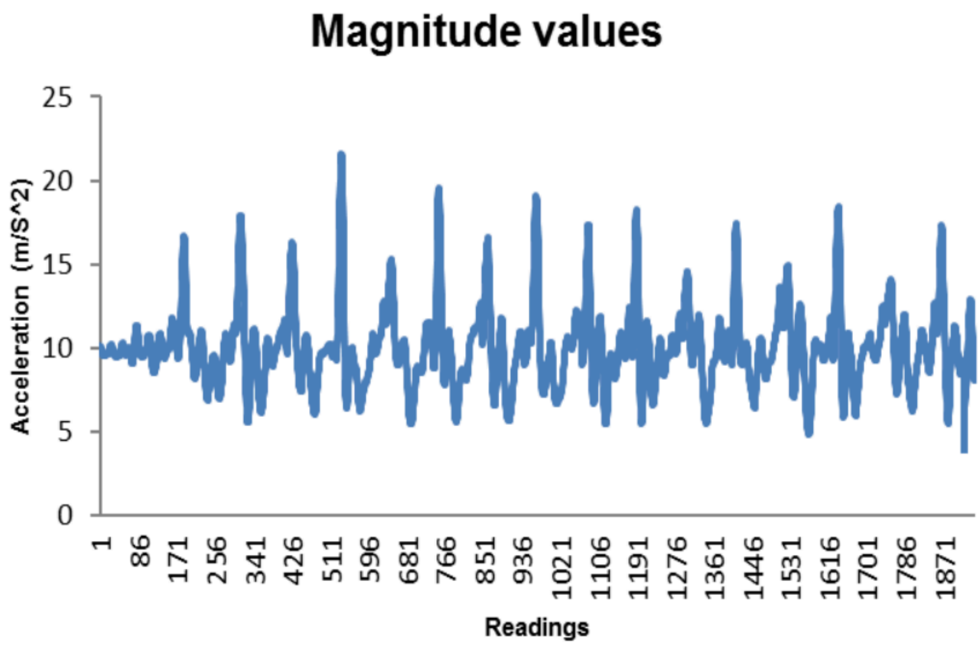

Figure 6: Magnitude values

In the next step, a digital low-pass filter is required to smooth the signals in Fig. 6. As the accelerometer sensor's high sensitivity to movements, smoothing the data is necessary for more precise peak detection.[**3**]

Next, we need to monitor the maximum and minimum acceleration values over a specific number of samples (e.g., 100) in all three axes. Define the dynamic threshold level as the average of these values. Then, this threshold is used to determine if steps are taken in the next 100 samples. Since this threshold updates every 100 samples, it is referred to as a dynamic threshold. If there is a negative slope of the acceleration, a step is detected. Additionally, for increased accuracy, dynamic precision could be employed. This parameter measures how fast the acceleration is changing, and decides if it's a proper step or just a random movement.

Although it works well, it is sensitive to false movements. For instance, if the pedometer vibrates rapidly or slowly due to reasons other than walking, the step counter may mistakenly take it as a step. To solve this issue, we implement a time window and count regulation. We assume that people can walk as fast as five steps per second and as slowly as one step in two seconds. Therefore, the time window is set between [0.2s to 2s], and signals outside of this interval are considered as noise.[**4**] Here is a simplify implementation of the algorithm above:

1. Calibration
2. Data collection(X, Y, Z axis): Retrieve data from the X, Y, and Z axes, filtering and refining those values.
3. Dynamic threshold calculation: Identify the maximum and minimum values for all axes and calculate dynamic threshold.
4. Sample counter check: Check if the sample counter equals 100.
5. Step counting Compare the Max and Min values with the threshold values to determine the step count.

And here is the C++ code of the above algorithm:

```
void calibrate_accelerometer() {

    // Define number of samples(here, 100 samples)
    const int numSamples = 100;

```

```
// Define arrays to store x, y, and z values
// in each iteration
float xval[numSamples];
float yval[numSamples];
float zval[numSamples];

float sumx = 0.0;
float sumy = 0.0;
float sumz = 0.0;

for (int i = 0; i < numSamples; i++) {
    xval[i] = float(analogRead(xpin) - 345);
    sumx += xval[i];

    yval[i] = float(analogRead(ypin) - 346);
    sumy += yval[i];

    zval[i] = float(analogRead(zpin) - 416);
    sumz += zval[i];
}

// Cumpute dynamic threshold
float xavg = sumx / numSamples;
float yavg = sumy / numSamples;
float zavg = sumz / numSamples;
}
```

3.3.2 Calories Measurement

Smartwatches use acquired data from heart rate and fitness tracking to measure burned calories. In fact, during intense physical activity, your heart rate increases which leads to higher energy consumption. Thus, you are burning more calories. Therefore, two types of sensors are required to measure burned calories: a heart rate monitor and an accelerometer. The more accurate these two sensors are, the more precisely the calculation of burned calories can be determined.

In the following, there are two kinds of formulas for calculating burned calories using different parameters. It should be noted that these formulas can only be applied if the heart rate is between 90 and 150 bpm[7][**5**, **6**, **7**].

Calculate burned calories using HR, weight, and age, 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
```

Calculate burned calories using HR, VO_2max, weight, and age, 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
```

[7] beats per minute

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

Figure 7: Amuont of burned calories of 30 years and for 60 minutes of physical activity result

4 Conclusion

As PPG devices become widespread, there is a significant opportunity to monitor health and fitness in daily life. Clearly, the effectiveness of these devices depends on both their hardware architecture and usage. PPG signals estimate various physiological parameters and helped us learn more about the human body in recent years. Smartwatches are valuable in detecting arrhythmias and diseases, which emphasizes the growing importance of these devices. Furthermore, we can expect continuous improvements in this field. Hopefully, in the future, smartwatches can measure all physical parameters, reducing the necessity for in-person doctor visits and check-ups.

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] Swain DP, Abernathy KS, Smith CS, Lee SJ, Bunn SA. Target heart rates for the development of cardiorespiratory fitness. Med Sci Sports Exerc. January 1994. 26(1): 112-116.

[7] Subir Biswas. How do Smartwatches Measure Calories | Tech-Knowledge. Jan 3, 2022.

[8] Nicolas de Pinho Ferreira, Bertrand Massot, Claudine Gehin. A Review of Methods for Non-Invasive Heart Rate Measurement on Wrist. Institut National des Sciences Appliquées de Lyon.