Electrode Comparison for Heart Rate Detection via Bioimpedance Measurements

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***Abstract*—Compact wrist-worn devices that can continuously measure human bio-parameters such as heart rate offers valuable health information and facilitate healthcare outside clinical settings. Bioimpedance is a promising alternative sensing modality for vital signs monitoring in wearable devices but requires close proximity to the subject's skin. The current study evaluates the suitability of different types of electrodes for on-wrist heart-rate measurements via bioimpedance. We compare copper, gold, and stainless steel electrodes with smooth and bumpy surfaces. To this end, we develop a signal-to-heart-rate data processing pipeline and a SNR-based metric that algorithmically evaluates the signal's quality. The results show that while there is a clear trend in the data that supports the selection of stainless steel over other metals and bumpy over smooth electrode surfaces, most of the variance in the signal quality comes from factors other than the electrode type.**

***Index Terms*—electrodes, bioimpedance, heart rate, wearable device**

I. Introduction

Cardiovascular illnesses are among the most widespread diseases in the world, necessitating the development of equipment that can more readily monitor crucial bio-parameters such as heart rate, blood pressure and breathing. Although this equipment is readily available in medical facilities, patients are typically no longer monitored after they leave these facilities [1]. Bioimpedance measurement is a promising technique for detecting not just the composition of tissues, but also the heart rate and other vital signs in human subjects. Compared to other techniques for vital signs monitoring, bioimpedance has the potential to enable wearable devices with lower power consumption, which is a significant benefit for continuous measurements. As a result, bioimpedance enabled wrist-worn measurement devices hold the promise of conveniently monitoring human bio-parameters outside of clinical settings, and also to other functions such as exchange of data via Body Coupled Communication (BCC) [2]. However, the development of bioimpedance-enabled wearable devices is challenging due to several factors, such as the choice of appropriate electrodes, their configuration, location, power supply, the weight of the whole system and its accuracy.

This work is an experimental study that examines the impact of the electrode type for heart rate monitoring from bioimpedance signals obtained on the wrist. To put it in the context of related work, the problem of wrist-based non-invasive heart rate measurement has attracted a large attention from the research community. Nine different methods including electrocardiography (ECG), photoplethysmography (PPG), ultrasound, and impedance plethysmography are described in De Pinho Ferreira *et al.* [3]. The mechanism behind impedance plethysmography relies on measuring the impedance changes in tissue caused by changes of blood volume in arteries. During the systolic phase of the heartbeat, blood flow increases, resulting in a lower impedance, and vice versa for the diastolic phase. The impedance changes are measured by passing a low voltage alternating current (AC) through human tissue and observing how the impedance changes with time. It was found that results depend on the size and the positions of the electrodes [3]. Typical AC frequencies are from 10 to 100 kHz. Both two-electrode (bipolar) and four-electrode (tetrapolar) setups are possible. The tetrapolar setup is preferable, because it allows to eliminate contributions from the electrode–tissue interface. In low frequencies and with small electrodes these contributions can dominate the measurement [4]. However, two-electrode setups allow measurement devices with smaller form factors, and reduce the probability that the contact between skin and the electrodes is lost. For wearables, so-calling "polarizable" electrodes that do not allow the passage of charge carriers through the skin-electrode interface are typically used. In contrast, ECG typically uses electrodes that rely on reduction or oxidation reactions, and are not suitable for long-term wearing as they suffer from chemical degradation. The paper by Cho *et al.* [1] is one of the first where feasibility of wrist-worn bioimpedance measurement devices is investigated. A small-scale four electrode setup is used and electrode locations are optimized. The performance of such wearable devices depending on electrode size, spacing and AC frequency is investigated in Wang *et al.* [5]. Alharbi *et al.* [6] had conducted a relatively large-scale study with 51 test subjects. Multi-stage signal processing procedure for heartbeat detection was adopted and results were validated with a digital blood pressure measurement device. In many existing works, for instance, in Huynh *et al.* [7] similar setups are used to measure both, pulse-wave velocity and the heart rate. In other works, for example, in Gonzalez-Landaeta *et al.* [8] heart rate detection algorithms are applied to bioimpedance measurements performed with a tetrapolar electrode connection with feet as the contact surface.

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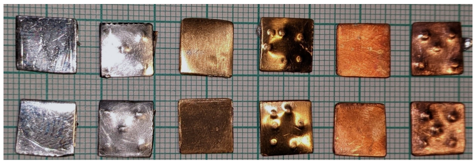


Fig. 1: Electrodes used in the experiments.

Compared to the studies mentioned above, the current study utilizes a bipolar electrode setup in contrast to the typical tetrapolar one. Our main motivation lies in the observation that the tetrapolar setup sacrifices user convenience for measurement accuracy. We envision that a smaller and better-fitting wearable strap is possible when using just two electrodes. We focus on the material and surface type of polarizable electrodes, and experimentally investigate stainless steel, gold and copper electrodes with both smooth and bumpy surfaces. Empirical mode decomposition (EMD) is utilized to decompose the raw signals and obtain beats-per-minute (BPM) information from the raw signals. Signal-to-noise ratio (SNR) on the autocorrelation function of the processed signals is used to assess the quality of each signal.

The paper is structured as follows: Section II describes the experimental setup and data analysis methods; Section III presents and discusses the results; Section IV concludes the paper.

II. Methods and Materials

A. Electrodes

We started the work by creating several pairs of electrodes (Fig. 1) from different materials. The dimensions all electrodes are 10 x 10 x 0.4 mm. Three types of materials are used: (1) stainless steel; (2) copper; (3) copper electroplated with a thin gold layer, referred to as "gold electrodes" further in this work.

On top of the different materials, two types of electrode surfaces are investigated: (1) smooth surface; (2) rough surface with mechanically created bumps. Several small bumps are created on the surface of each electrode. Overall, we compare six types of electrode pairs.

B. Measurements

We measure bioimpedance with the Zurich Instruments MFIA 500 kHz / 5 MHz Impedance Analyzer [9]. The equivalent electrical circuit of the measurement setup is shown in Fig. 2. We use 100 kHz sine wave with amplitude of 0.3 V as the generated signal, as these are common values for bioimpedance applications [10], [11]. The measurement setup is as follows (Fig. 3):

1) A pair of each electrode type is selected and soldered to test leads. The test leads are put in a test fixture to keep an approximate distance of 1 cm between the electrodes. The distance is selected to match potential wearable applications in the future.
2) The electrodes are cleaned with alcohol and a thin layer of ECG gel [12] is applied on the surface of each electrode.

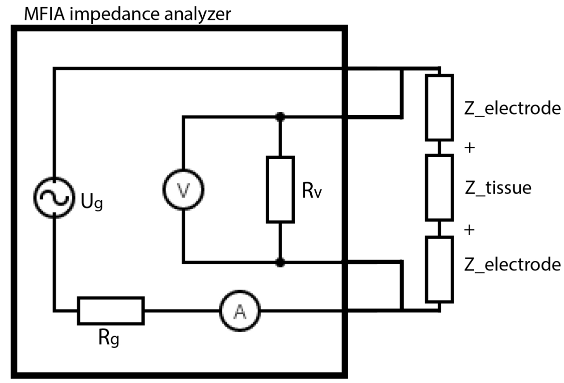


Fig. 2: The equivalent circuit of the measurement setup.

Fig. 3: Conceptual overview of the experimental setup with the electrodes and MFIA impedance analyzer.

3) A volunteer test subject places the electrodes on their left hand wrist, and the experimenter applies a tourniquets to fasten the electrodes firmly in place.
4) The test subject also takes a Maxim Integrated MAX30102 [13] PPG sensor and clamps it between his thumb and forefinger to record his ground-truth heart rate.
5) The system is briefly ($\approx$ 1 min) allowed to settle.
6) The test subject sits still for 20 seconds while bioimpedance and PPG signals are recorded.

We record the signals on two male volunteers, for each of them on three different days.

C. Data Processing

Four different bioimpedance signals are recorded by the MFIA device: real part and imaginary part of the complex impedance: Real(Z) and Imag(Z); magnitude of the impedance: ABS(Z); and phase of the impedance: Phase(Z).

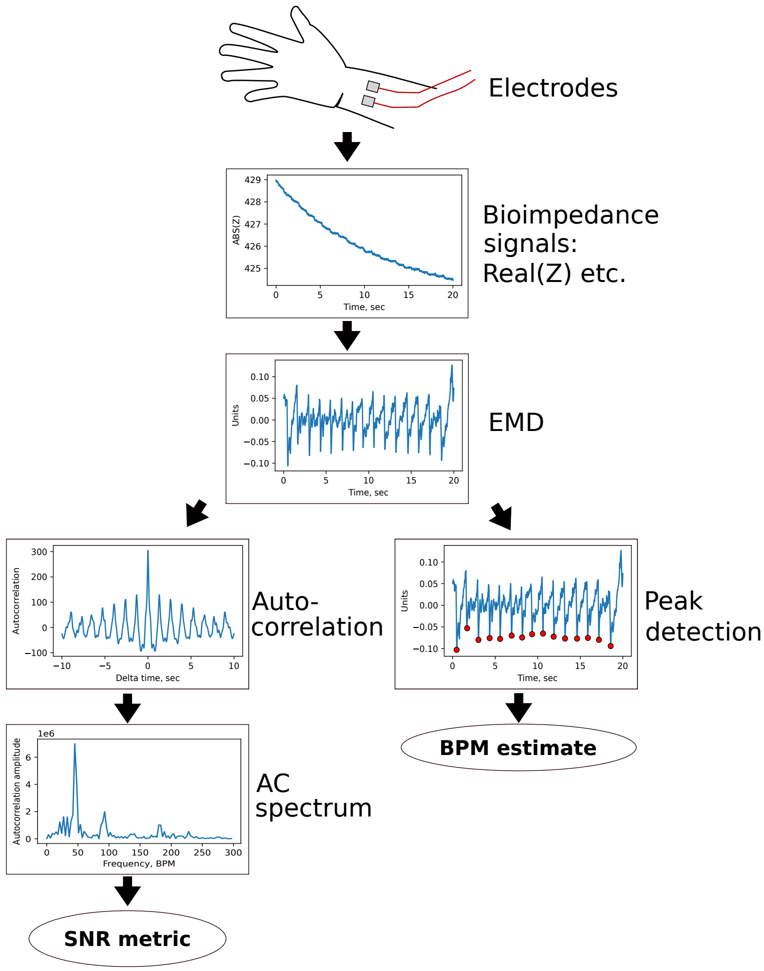


Fig. 4: Overview of the data processing pipeline.

A multi-stage approach in MATLAB is implemented in order to evaluate a human heart rate from these raw bioimpedance signals (Fig. 4).

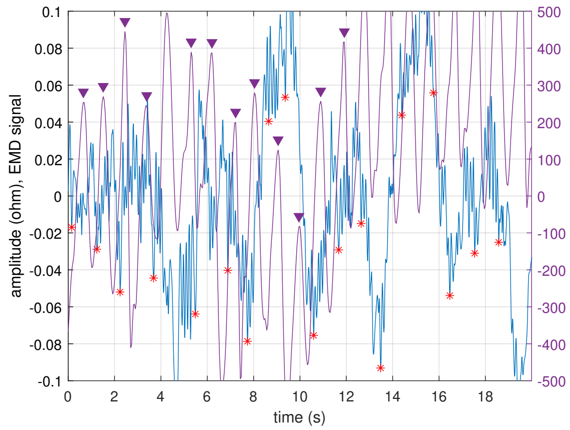
1) Empirical Mode Decomposition: The raw signals are not immediately usable for heart rate detection via peak detection or similar methods due to the large amount of noise. Not all standard techniques for noise removal are applicable to the problem. For instance, FFT-based bandpass filtering cannot be used because the heart rate signal is not easily decomposable in low-frequency sine waves. Hence, a key technique in our arsenal for removing the noise is Empirical Mode Decomposition (EMD), which is useful for processing non-stationary, non-linear signals. As a result of EMD, the so-called intrinsic mode functions (IMFs) corresponding to different frequencies and a residue are extracted. The IMFs represent oscillating components of various magnitudes embedded into the analyzed signal. A detailed explanation of EMD and its applications in medical signal processing can be found in [14] and [15]. Signal, decomposed into n number of IMFs and a residual term r can be written as follows:

$$x(t) = \sum_{j=1}^{n} IMF_j + r_n \tag{1}$$

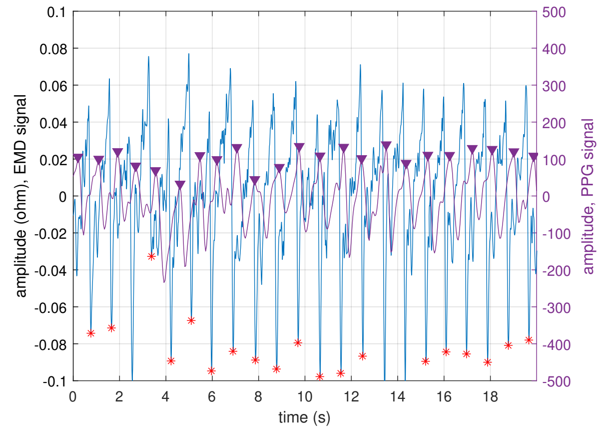
The `emd` MATLAB function is used to extract the IMFs and the residual term. Signal noise, presumably contained in the lower-order IMFs is filtered out by summing only the higher order IMFs, specifically, those with orders from two to five.

2) Signal Quality Estimation: The result of the EMD still contains a relatively large amount of noise. We run a two-stage process to estimate the quality of the EMD result. First, we apply autocorrelation on the EMD signal. We expect to see peaks in the autocorrelation result due to the periodical nature of the heart rate signal, with the period between peaks corresponding to the heart rate period in seconds. Intuitively, the more pronounced these peaks are, the more suitable the signal is for heart rate detection. To measure the intensity of the peaks, we apply FFT to the autocorrelation result and use the magnitudes of the result. Subsequently, we search for a peak amplitude A_{signal} in the FFT in the frequency range from 0.66 Hz to 1.5 Hz. This frequency range corresponds to heart rate of 40 to 90 BPM, as for an adult subject in a resting state the true BPM value is expected to be in this range. The signal-noise-ratio (SNR) is then calculated as:

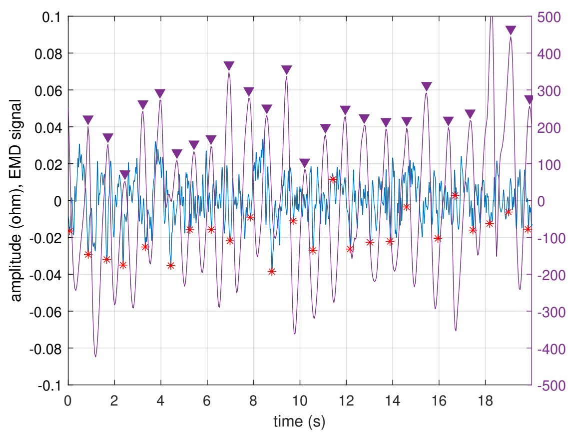
$$SNR = 20 \cdot \log_{10} \frac{A_{signal}}{A_{noise}}, \tag{2}$$



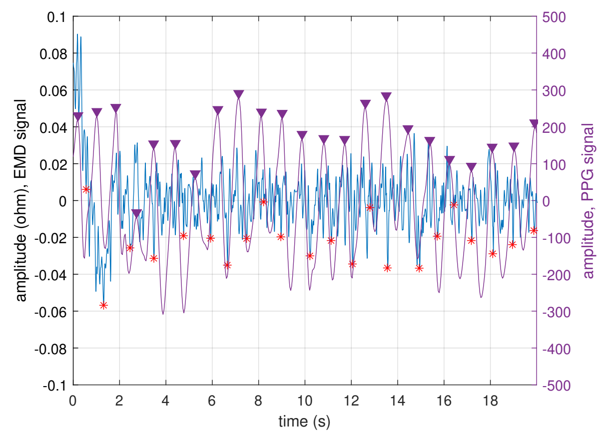
(a) Copper, bumpy (SNR 73.2 dB)



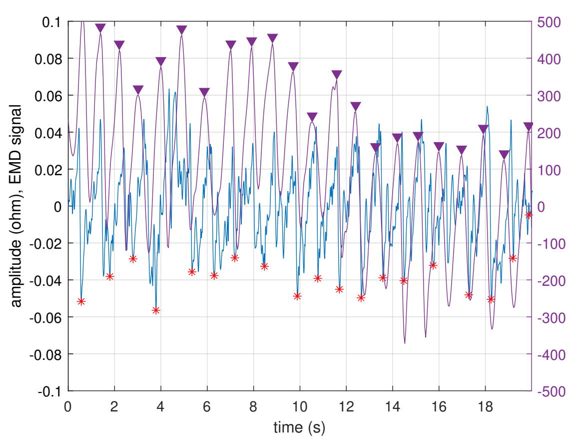
(b) Copper, smooth (SNR 93.1 dB)



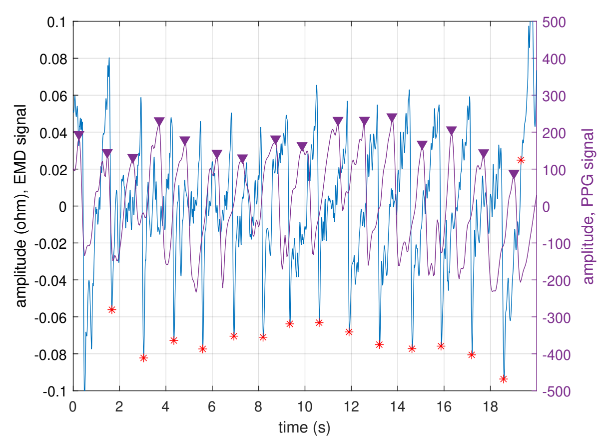
(c) Gold, bumpy (SNR 84.8 dB)



(d) Gold, smooth (SNR 75.7 dB)



(e) Stainless steel, bumpy (SNR 87.1 dB)



(f) Stainless steel, smooth (SNR 88.2 dB)

Fig. 5: Heart rate signal depending on the electrode type. EMD data of the bioimpedance signal (Real(Z)) shown in blue, simultaneously measured PPG data shown in purple, along with peaks detected on the PPG data and inverted peaks on the EMD data. Representative data from a single test subject in a single day.

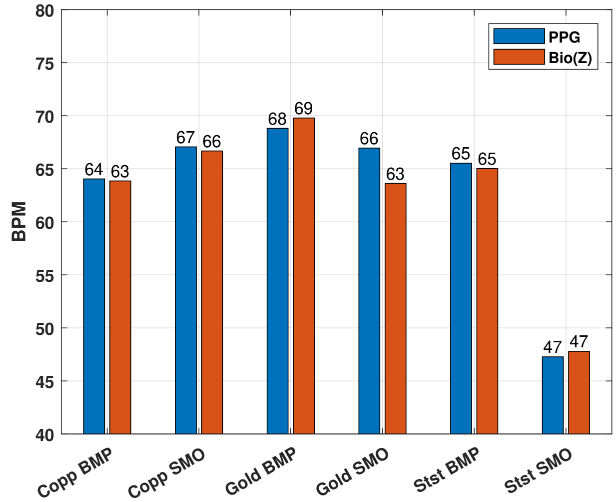


Fig. 6: Comparison between the BPM estimated by our method and the BPM measured by the PPG sensor. Same subject and day as in Fig. 5. Peak detection applied on the best signals selected by SNR.

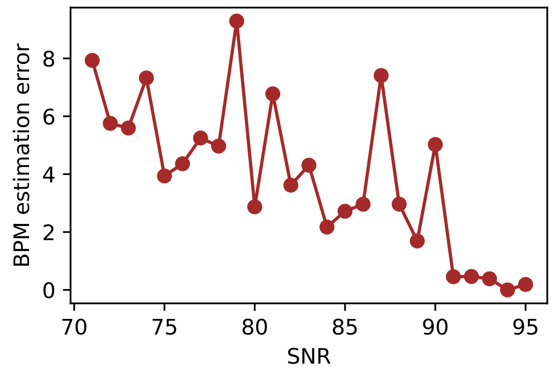


Fig. 7: The dependence of the BPM estimation error on the SNR metric, average results for all test subjects on all days. The error is measured relative to the PPG sensor.

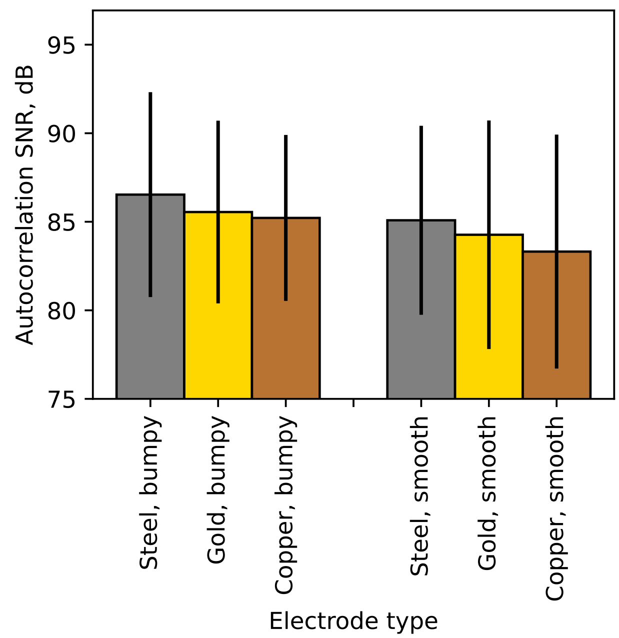


Fig. 8: SNR based quality estimate of the different electrode types.

where A_{signal} is the amplitude at the peak frequency and A_{noise} is the average amplitude at all other frequencies, excluding the DC component.

3) Heart Rate Estimation: From the four signals that are recorded in each experiment, the signal with the highest SNR is used for the heart rate estimation. The heart rate in beats per minute (BPM) is estimated using inverted peak detection on the EMD signal using the `findpeaks` MATLAB function on the signal multiplied by -1. A minimal peak interval of 0.7 seconds is used. To obtain BPM from the peaks, we calculate d, the average time difference between peaks detected in the experimental interval. The duration of the interval in minutes is divided by this to estimate the BPM value: $BPM = 60/d$.

III. Results and Discussion

A. Heart Rate Signals

Fig. 5 shows the EMD signals (blue) obtained from the raw Real(Z) data recorded by the MFIA impedance analyzer in a single experimental session. Along the EMD signal, PPG values (purple) are plotted as a ground-truth, for comparison and validation. Peaks detected by the peak detection algorithm are marked in the figures with triangles. The axes of all graphs have the same scales on y-axis, -0.1 to 0.1 on left for EMD signals, and -500 to 500 on the right for PPG signals.

The duration of each measurement is 20 seconds. Even though the PPG and EMD signals are taken simultaneously, the peaks of both signals are not expected to perfectly match for two main reasons: (1) the PPG data measurement system has a small delay when obtaining the information through the Matlab interface due to the delay in the code installed in the microcontroller; (2) bioimpedance data is obtained above the left hand wrist (Fig. 3), but the PPG data is obtained from thumb. The pulse wave is expected to have a noticeable delay comparing the travel times from the wrist and fingers.

The bioimpedance signals measured with the smooth copper electrodes (Fig. 5b) and the smooth stainless steel electrodes (Fig. 5f) have the most adequate visual appearance, and also the highest SNR metrics. The real part of bioimpedance signals measured with the bumpy copper electrodes (Fig. 5a) is very chaotic with very low corresponding SNR. Curiously, the other components of the signal from these electrodes, such as the Imag(Z) component have much higher visual quality and SNR. The results obtained with other electrode types are in between these two extremes in their visual quality and their corresponding SNR values.

We confirm that the SNR metric matches with human intuition about what makes a good heart rate signal by asking two volunteers to rank the measured bioimpedance signals by their perceived visual quality, and comparing this ranking with the ranking produced by the SNR metric. While the differences in the ratings between the SNR metric and either of the reviewers are slightly larger than the rating differences between both reviewers, the SNR/human rating match is reasonably good.

Fig. 6 shows that our BPM estimation results have a relatively good match, especially for the higher quality signals, with the PPG sensor values which we treat as the ground truth in these experiments. Fig. 7 shows that there is a relation between the SNR metric and the accuracy of the BPM estimation (Pearson's correlation $r = -0.28$). In particular, high SNR measurements show very good match ($\leq$1 difference) between the BPM estimated via our method and the BPM obtained from the PPG sensor.

B. Electrode Quality Comparison

In order to compare the different types of electrodes, we aggregate the SNR results from all six experiments, each experiment with six types of electrode pairs. Instead of preselecting to use *e.g.*, Real(Z) signals for each of these results, we compute EMD on all four bioimpedance signals, namely Real(Z), Imag(Z), Phase(Z) and Abs(Z) and then use the best EMD from these, as measured by the SNR on its autocorrelation. This allows to reduce the impact of external factors on the results.

Fig. 8 shows the average SNR values and their standard deviations for each electrode type. A clear picture emerges:

- Bumpy electrodes have better average performance than smooth electrodes;
- Steel electrodes outperform gold electrodes, which, in turn, outperform copper electrodes.

It is important to stress that these are preliminary results that need further confirmation. In particular, the variability between the experiment days and the experiment subjects (as shown by the standard deviations in Fig. 8) is larger than the variability between the different types of electrodes. This is likely to be the effect of slightly different electrode placements on the wrist; as known in the research literature, the placement has a large impact on the results [3]. We did not attempt to perfectly match the locations of the electrodes between the measurements, as it is unlikely that real users of such devices would be able to do that.

Another aspect to note is that for gold electrodes the performance degraded noticeably over time. For instance, in the first experiment, gold electrodes showed the best results. In subsequent experiments, the gold plating on these electrodes started to degrade, as observed visually, and the result quality decreased. If proper gold electrodes are used instead the copper ones with a gold plating, the results may differ.

IV. Conclusion

This paper focuses on electrode selection for wrist-worn bioimpedance measurement applications. To this end, we create six different pairs of electrodes, and conduct a small experimental study with two test subjects and three data recording sessions for each of the subjects. We analyze the data by estimating the beats per minute (BPM) from empirical mode decomposition (EMD) of the signals, and quantify the quality of the data by a signal-to-noise ratio (SNR) metric computed on the autocorrelation of the EMD. The BPM estimation results are validated with a photoplethysmography sensor, and we observe low BPM estimation errors ($\leq$1 BPM) at a high SNR ($\geq$90 dB), with progressively larger ones at lower SNR levels. Our preliminary findings suggest that the stainless steel electrodes are more suitable than the gold ones, which in turn are better than the copper ones, and that bumpy surface is better than smooth. However, there is a large variation in signal quality that is dependent on other factors. In summary, while the type of the electrode clearly matters, it is just one of the ingredients necessary to accurately estimating heart rate from bioimpedance signals. In the future work, we will extend the comparison to also include tetrapolar setups.

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