Data Compression for Wireless ECG Devices

Elena Merdjanovska[1,2][a], Miha Mohorčič[1], Matjaž Depolli[1][b], Aleksandra Rashkovska[1][c] and Tomaž Javornik[1][d]

[1]*Department of Communication Systems, Jožef Stefan Institute, Ljubljana, Slovenia*

[2]*Jožef Stefan International Postgraduate School, Ljubljana, Slovenia*

Keywords: ECG, Wireless, BLE, Compression, Delta Coding.

Abstract: Wireless ECG devices are the latest novelty in the field of electrocardiography. ECG is commonly used in healthcare systems to observe cardiac activity, however wireless devices bring new challenges to the field of ECG monitoring. These challenges include limited battery capacity, as well as increased data storage requirements caused by daily uninterrupted ECG measurements. Both of these issues can be mitigated by introducing an efficient compression technique. This paper explores two direct data compression methods for ECG data: delta coding and Huffman coding, as well as their variations. We performed experiments both on measurements from a wireless ECG sensor – the Savvy ECG sensor, as well as on measurements from a standard public ECG database – the MIT-BIH Arrhythmia Database. We were able to select suitable parameters for delta coding for efficient compression of multiple ECG recordings from the Savvy ECG sensor, with a compression ratio of 1.6.

1 INTRODUCTION

Electrocardiogram (ECG) recordings capture the electric potential on the body surface, which changes as a result of the electrical activity of the heart (Trobec et al., 2018b). ECG is the most common and extensively used vital sign monitoring representation in modern healthcare systems and various ECG measurement formats exist. The standard 12-lead ECG is used to provide information on cardiac activity during a short-term monitoring from 12 different perspectives (leads), whereas Holter ECG records the electrical activity of the heart over longer period of time (several hours) from 5-7 leads. In addition to these two methods, which are currently most widely used in clinical practice, novel small wireless ECG body sensors are being developed. An example of such a sensor is the Savvy ECG sensor (Rashkovska et al., 2020), developed at the Jožef Stefan Institute (Fig. 1).

Wireless ECG body sensors, as well as their broader and more frequent use than traditional ECG-monitoring methods, pose new challenges. It is well-known that wireless data communication takes up a large part of the total power consumption in most portable wireless devices. By compressing the data prior to wireless transmission, power can be saved assuming that the compression operation itself does not consume too much power. In addition, large volumes of ECG data are being recorded using these new measurement devices, which must be compressed for efficient processing and storage. It can be concluded that compression is a very significant topic in computational ECG analysis, most notably in the case of wireless ECG devices.

The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant signal morphology features upon reconstruction. Data compression techniques have been utilized in a broad spectrum of communication areas such as speech, image, and telemetry transmission (Jalaleddine et al., 1990). Existing data compression techniques for ECG signals lie in two categories: direct data and transformation methods. Direct data compression techniques for ECG signals have shown a more efficient performance than the transformation techniques in regard to processing speed and compression ratio. Direct data compressors detect redundancies by a direct analysis of the actual signal samples. In contrast, transformation com-

[a] https://orcid.org/0000-0003-0794-8438
[b] https://orcid.org/0000-0002-0365-5294
[c] https://orcid.org/0000-0002-2014-8630
[d] https://orcid.org/0000-0002-8676-5658

Merdjanovska, E., Mohorčič, M., Depolli, M., Rashkovska, A. and Javornik, T.
Data Compression for Wireless ECG Devices.
DOI: 10.5220/0010818100003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 4: BIOSIGNALS*, pages 15-21
ISBN: 978-989-758-552-4; ISSN: 2184-4305

pression methods mainly utilize spectral and energy distribution analysis for detecting redundancies. Different transforms have been used for this purpose in the literature, such as Fourier, Wavelet (Rajoub, 2002) and Cosine transforms (Ranjeet et al., 2011). In addition, other methods such as compressed sensing (Mamaghanian et al., 2011) have been employed for ECG compression.

Figure 1: Savvy ECG sensor in use.

In this paper, the focus is on novel signals obtained from a wireless single-lead ECG sensor, namely the Savvy ECG sensor, where compression options are limited by the properties of the implemented data transmission method on the ECG sensor (Vilhar and Depolli, 2018). The sensor transmits the sampled data in packets and does not re-transmit the packets that get lost due to insufficient quality of the wireless data connection. Therefore, the compression has to be resilient to missing data and has to work on chunks of very limited size. In addition, the calculations, necessary to perform the compression, need to be done on an embedded low power device. As a result, a large portion of state-of-the art compression techniques, mainly transformation-based techniques, are unsuitable in this case because of their computational complexity. Thus, we focus on direct data compression techniques for ECG: delta coding, and the most popular type of entropy coding – Huffman coding. These two methods do not require high calculation power and can be applied even in the case of lost packets.

The paper will provide an overview of how these data compression techniques work, as well as how they perform on example signals from the Savvy ECG sensor, and also on ECG recordings from a standard public database. The aim is to assess and discuss whether and how this techniques could be used for a mobile ECG device, mainly focusing on compression prior to transmission, but also for efficient storage. This makes this study very significant since it examines compression with a unique combination of limitations: compression before transmission, dealing with packet loss and testing on novel ECG body sensor measurements, all of which are rarely found in other works. In addition, possible future steps towards efficient transmission of differential ECG from a wireless sensor will be identified.

2 SINGLE-LEAD ECG SENSOR DATA

The Savvy ECG sensor is a body gadget with two self-adhesive electrodes, powered by a rechargeable battery. It uses a Bluetooth Low Power (BLE) radio transceiver for communication (Rashkovska et al., 2020). The measured ECG signal is a difference between the electrical potentials of the two electrodes. The analogue signal is converted into a 10-bit digital sample, and the signal is then streamed to a personal digital assistant (PDA), like a smartphone or a tablet, through the BLE connection. The default sampling rate was chosen to be 125 samples/s – a compromise between sustainable power consumption and acceptable measurement quality. If required, the sampling rate can be increased up to 1000 samples/s. For this study, we used 4 measurements sampled at 256 samples/s, which contained segments with high levels of noise. For future work, other sampling rates should also been examined, as well as compression for noise-filtered signals, since better reconstructed signal quality could potentially be obtained in that case, using the same methods. For this study however, we decided to focus on only one frequency, since the methods presented are frequency specific, especially key parameters such as the number of bits needed to represent the difference values.

As defined in the data stream specification of the PCARD wireless protocol(Trobec et al., 2018a), each packet transmitted via BLE contains 140 bits data samples (14 10-bit samples without compression). In order to compare how well the methods perform on a standard public ECG database, the experiments were run on 5 recordings from the MIT-BIH Arrhythmia Database, which contains recordings with 11-bit resolution and sampling rate of 360 samples/s. However, in the description of the methods in the next sections, the specifics and the given examples will be shown only considering the data from the Savvy sensor.

3 METHODS

In the following section, the direct data compression methods will be presented. First, delta coding will be explained, covering both the one-level variant and the high-and-low-level variant. For each, the proposed packet for the compressed data before transmission is also presented. Furthermore, an overview of Huffman encoding will also be given.

3.1 Delta Coding

ECG is a waveform signal and successive samples mostly have small differences between them. Having this in mind, delta coding can be applied to reduce the dynamic range of original ECG signals. With delta coding, proposed for the first time in (Fang and Lu, 2018), subsequent encoded samples are generated from the difference between the current sample and the previous sample of the original ECG signal. This difference signal will have a much lower dynamic range than the original ECG signal, so it can be effectively quantized using a smaller number of bits. An ECG signal contains the P–QRS–T and U waves, where the minimal dynamic range is the P–Q or T–U wave, and the maximal dynamic range is the QRS complex. This compression method has been extensively used for ECG, commonly combined with other techniques, such as zero-separation (Fang and Lu, 2018) and most often Huffman coding (Chang and Lin, 2010).

In the specific case of the Savvy ECG signals, it was shown that the maximal difference can be encoded with 9 bits, due to the higher level of noise and relatively low frequency of 256 samples/s. In the case of the cleaner MIT-BIH recordings, with lower frequency of 360 samples/s, the largest delta could be encoded with as few as 8 bits. Having this in mind, we can conclude that, in general, for each actual difference in the original analogue signal, for the Savvy recordings we will always need 1 bit more than for the MIT-BIH database recordings. The calculation of the value differences is very simple, requiring only one pass over all values, which makes it suitable for implementation on an embedded low-power device such as Savvy.

In the following two sections, different variants of delta encoding will be presented, with the proposed packet format for the Savvy sensor.

3.1.1 Single Category

In single-level delta coding, each difference is encoded with the same number of bits, i.e., the number needed to code the largest difference that could appear in the signal. In the case of the Savvy example data, this is 9 bits. With higher frequencies, this number decreases. In the case of simple delta coding, each packet is 140-bit long. The first 10 bits are the anchor value – the value in the original signal. After that, 130 bits remain, in which around 14 9-bit differences can fit, making a total of 15 signal samples in one packet, as opposed to the original 14. This means that the compression ratio we can expect from this method is around 1.07.

The anchor value can also be transmitted only once in the first packet, with the following ones transmitting only delta values. This case does not allow for lost packets, since one lost packet will make all of the following incorrect. Due to this, we decided to send an anchor with each packet.

3.1.2 Low and High Categories

In this paper, additional experiments were done with a variant of delta coding, where two levels of differences are introduced, as proposed in (Hatim et al., 2016). The main idea of this scheme is to utilize the parts of the ECG signal with smaller dynamic range, by encoding those differences with less bits. This way two coding categories are created: low encoding, where lower differences in the signal are encoded with as few bits as possible, and high encoding for the remaining differences. For each data sample, the difference is calculated and it is determined whether it belongs to the low category (lower than some threshold value) or to the high one. The number of bits for the high category is the same as the one used in single-category delta encoding – 9-bits in the case of Savvy.

To determine the low-encoding bits, an analysis of the delta values present in the signal needs to be performed. In Figure 2, the distribution of the absolute values of the differences present in one Savvy recording is shown. Each bar corresponds to the values that can be coded with the same minimal number of bits, in order to see which difference bit-widths are most common. For example, the sixth bar ranges from 32 to 64, meaning the actual differences falling in that interval are [-64,-32) and [32,64) and can be represented with a minimum of 7 bits ($2^5 = 32$ + one sign bit). From the distribution graph, we can see that possible low encoding bit-widths are 3, 4 and 5. In addition, we can see that the large delta values very rarely appear in the signal, which could mean they are a result of noise. Due to this, it is possible to decrease the number of bits representing the high category, by introducing a very small error (loss) in the decompressed signal. This is also true for single-level delta encoding and this possibility for lossy delta compression will be explored in Section 5.

In order to differentiate between different coding categories, the transmitted packet must be structured with specific fields. In Figure 3, the proposed packet format for 2-level delta encoding is shown. Each

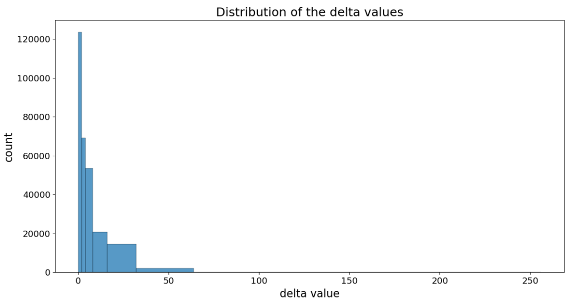

Figure 2: Distribution of the delta values in an example Savvy signal.

packet starts with an anchor value, which is 10-bit value from the original signal, followed by a window size, indicating how many consecutive differences of the current category are given. In this case, we set the window size to 6-bits because the maximal number of low-category deltas that can fit in one packet (140 bits) is never more than 41 (when low category is 3 bits). In addition, the interval between neighboring heartbeats is around 0.8 seconds on average, which in the case of Savvy data equals to around 200 signal samples. This means that on average, between two clean heartbeats, we need to change the category at least 5 times, each time we construct a new packet, when in reality the delta category of the actual signal does not change. The overhead introduced with each category change is around 5% (7 bits) of the entire packet, and this overhead is added many more times than actual changes of category in the signal.

The anchor value in each packet was included as a safety mechanism in case of a data stream packet loss, so that the damage does not affect received samples from other packets. However, this comes at a cost of not being able to entirely utilize the advantages of two-level delta encoding, as well as delta encoding in general.

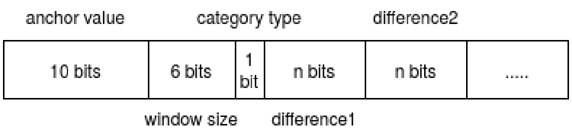

Figure 3: Packet format of two-category delta coding.

On Figure 4, we can see an example of the distribution of the length of the windows in one Savvy signal, when two-category delta coding is applied (low: 5 bits, high: 7 bits). We can see that the longest windows (consecutive deltas in the same category) are almost always from the low category, while most of the high-category windows are among the shortest. This behavior is desired and confirms the potential of two-level delta coding.

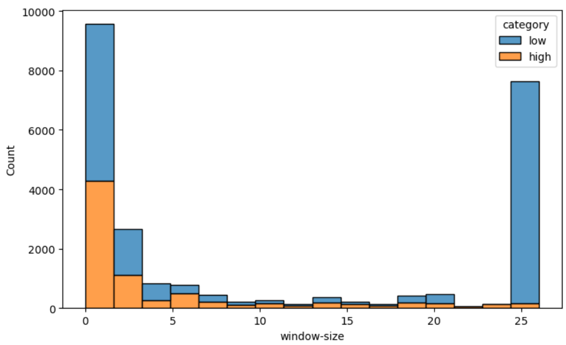

Figure 4: Distribution of the length of the windows in low and high categories separately.

3.2 Huffman Coding

Huffman coding is an entropy encoding algorithm used for lossless data compression (Jalaleddine et al., 1990). It creates variable-length codes with shorter code words for higher probabilities, and each is represented by an integer bit number. A Huffman code is generated by constructing a binary tree. The path from the root to each leaf in the tree gives the codeword for the bit sequence of the edges passing through the path. This type of coding is also resistant against packet loss, since each value is assigned a predefined code, independent of the values in the other packets.

4 PERFORMANCE METRICS

In general, compression results in a compromise between efficiency and quality. Due to this, it is necessary to calculate both of them (Němcová et al., 2018). The main metric used for the evaluation of compression efficiency is the compression ratio (CR). The compression ratio is defined as:

$$CR = \frac{original}{compressed} \tag{1}$$

In our case, the original and compressed data can be measured in the total number of bits, or the number of BLE packets, as defined in Section 3.1, needed to transmit the same data. The two compression ratios should be close in value, which is why only one was chosen, and the CRs given in Section 5 are the packet-level compression ratios.

To evaluate the quality of the decompressed signal, Percentage Root Mean Square Difference (PRD) was used. PRD takes into account the mean of the signal and the offset. It is defined as:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}[x(n)-\bar{x}(n)]^2}{\sum_{n=1}^{N}[x(n)]^2}} * 100 \tag{2}$$

, where $x(n)$ is the original signal and $\bar{x}(n)$ is the deconstructed signal.

The main goal of compression is to increase the compression ratio as much as possible, while keeping the diagnostic value of the ECG. Thus, small enough values of PRD do not affect the main ECG characteristics and, in those cases, the compression does not reduce the ability to detect heart abnormalities and arrhythmia from the ECG waveform. For atrial fibrillation (AF) detection, it has been shown that PRD up to 30% is acceptable and does not degrade RR-interval based AF detection performance (Cervigón et al., 2021). For other tasks such as QRS detection (Elgendi et al., 2017) and arrhythmia classification (Yildirim et al., 2019), it has been shown that PRD of up to 0.53% and 0.75% respectively does not influence classification and detection performance at all.

5 EXPERIMENTS AND RESULTS

In this section, the results for a few experimental setups of delta and Huffman coding are presented. In addition, data from two sources are included: recordings from the single-lead Savvy sensor, which is the main concern of this paper, and recordings from the standard MIT-BIH Arrhythmia Database, in order to examine how slightly different recording conditions affect the compression performance.

In Tables 1 and 2, the compression results from the standard version of both delta and Huffman coding are shown. Single-category delta coding is examined with a few different parameters, more specifically with 6, 7, 8 and 9 bits to represent each difference value. From the analysis described in Section 3.1.1, we were able to conclude that the maximum number of bits required to code any delta value in the Savvy recordings is 9, while in the case of the MIT-BIH database, it is 8 bits. This can be seen again in Table 1 for Savvy and in Table 2 for the MIT-BIH database, where the PRD for the higher bit values is 0. What is interesting to see is that even for the lower numbers of bits (6 and 7), the PRD is not very high (up to 5%), while the compression ratio increases. With single-category coding with 6 bits, a maximum compression ratio of around 1.6 can be achieved on Savvy recordings, while 1.77 on MIT-BIH recordings. In addition, by examining the location of the errors between the original and decompressed Savvy signals, it could be concluded that they largely appear in the parts of the signal with a lot of noise. This confirms that the obtained maximum delta value of 9 bits is not representative of the changes in the ECG waveform, but it was caused by the noisier parts of the recording, which is why single-category coding with a lower number of bits for delta is a good solution for encoding normal ECG.

In addition, in Tables 1 and 2 also Huffman coding results are shown. It can be seen that Huffman results are comparable with single-category delta coding results, especially considering that it enables lossless compression, which was not entirely the case in delta coding. However, it is worth noting that the Huffman coding examined in this paper does not consider the memory of the device and building of frames. In addition, each Savvy sensor can have a slightly different signal baseline, which means that a different Huffman tree needs to be constructed for each device when using Huffman to the raw signal values. However, if we choose to do Huffman encoding on top of delta (one or two level), this problem could be avoided. The analysis of the combination of Huffman and delta (applying Huffman coding to the delta values) is out of the scope of this paper, but it is a direction worth exploring in the future.

In Tables 3 and 4, the experimental results for 2-category delta coding are presented. Different combinations of the following parameters of delta coding were examined: 3, 4 and 5 bits for the low category; and 7, 8 and 9 bits for the high category. We can notice that the compression ratios depend on the signal characteristics much more, i.e. less bits does not always mean better compression. In general, we can see again that the PRD(%) are very low, since this is an extension of the single-category delta previously discussed. The best compression ratios for each recording are highlighted. We can see that the best CRs in general are obtained with 7 bits for the high category and either 4 or 5 bits for the low category. In addition, we were able to confirm that, on MIT-BIH recordings, better compression ratios could be achieved, due to the better quality of the signals and higher sampling rate.

6 CONCLUSIONS

In this paper, an analysis of ECG data compression methods was given. The main focus was to examine whether and how two groups of direct data compression can be applied to ECG signals, more specifically recordings from a wireless ECG sensor. Different parameters for one- and two-category delta coding, as well as Huffman coding were compared, both according to the compression ratios and the quality of the decompressed signal. The compression obtained on the single-lead wireless sensor recordings was comparable using both delta and Huffman coding, in the best

Table 1: Compression results on 3 Savvy measurements using 1-level delta coding (6, 7, 8 and 9 bits for delta) and Huffman coding.

	Delta (1-level)								Huffman	
	6 bits		7 bits		8 bits		9 bits			
Recording	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)
Savvy1	1.6176	0.4643	1.3971	0.1830	1.2319	0.0146	1.1029	0	1.5032	0
Savvy2	1.6176	2.0115	1.3971	0.3526	1.2319	0	1.1029	0	1.3746	0
Savvy3	1.6176	0.2368	1.3971	0.0266	1.2319	0	1.1029	0	1.7369	0

Table 2: Compression results on 5 MIT-BIH Arrhythmia measurements using 1-level delta coding (6, 7, 8 and 9 bits for delta) and Huffman coding.

	Delta (1-level)								Huffman	
	6 bits		7 bits		8 bits		9 bits			
Recording	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)
100	1.7718	2.2288	1.5298	0.6799	1.3469	0	1.2055	0	1.706	0
101	1.7718	2.1405	1.5298	0.3453	1.3469	0	1.2055	0	1.5676	0
103	1.7718	4.3631	1.5298	2.0187	1.3469	0	1.2055	0	1.5231	0
105	1.7718	1.0757	1.5298	0.2086	1.3469	0	1.2055	0	1.4179	0
107	1.7718	5.2711	1.5298	2.6601	1.3469	0	1.2055	0	1.1753	0

Table 3: Compression results on 3 Savvy measurements using 2-level delta coding, with different low and high bit-levels (low: 3, 4 and 5 bits; high: 7, 8 and 9 bits).

	low: 3, high: 7		low: 4, high: 7		low: 5, high: 7		low: 3, high: 8		low: 4, high: 8		low: 5, high: 8		low: 3, high: 9		low: 4, high: 9		low: 5, high: 9	
Recording	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)
Savvy1	1.17	0.12	1.47	0.09	**1.47**	0.06	1.11	0.01	1.43	0	1.46	0	1.07	0	1.4	0	1.44	0
Savvy2	1.06	0.23	1.31	0.18	**1.4**	0.14	1.01	0	1.27	0	1.38	0	0.96	0	1.24	0	1.36	0
Savvy3	1.44	0	**1.64**	0.01	1.58	0.01	1.4	0	1.62	0	1.57	0	1.35	0	1.59	0	1.56	0

Table 4: Compression results on 5 MIT-BIH Arrhythmia measurements using 2-level delta coding, with different low and high bit-levels (low: 3, 4 and 5 bits; high: 7, 8 and 9 bits).

	low: 3, high: 7		low: 4, high: 7		low: 5, high: 7		low: 3, high: 8		low: 4, high: 8		low: 5, high: 8		low: 3, high: 9		low: 4, high: 9		low: 5, high: 9	
Recording	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)	CR	PRD(%)
100	1.45	0.46	**2.08**	0.38	1.81	0.36	1.42	0	2.05	0	1.80	0	1.38	0	2.02	0	1.78	0
101	1.29	0.31	**2.07**	0.28	1.80	0.23	1.26	0	2.04	0	1.78	0	1.22	0	2.01	0	1.77	0
103	1.25	1.48	**2.05**	1.25	1.78	1.27	1.22	0	2.02	0	1.76	0	1.18	0	1.98	0	1.75	0
105	1.12	0.19	**1.78**	0.18	1.70	0.16	1.08	0	1.74	0	1.68	0	1.04	0	1.68	0	1.66	0
107	1.08	2.36	1.40	2.11	**1.57**	1.53	1.02	0	1.34	0	1.54	0	0.95	0	1.27	0	1.50	0

case around 1.6. This compression ratio corresponds to PRD of less than 0.5%, which has been shown to be sufficiently low for ECG-based diagnosis.

From the experiments in this study, we were able to choose one set of parameters which work well on multiple recordings. This conclusion and parameters would later need to be confirmed on a larger number of recordings. Other frequencies and noise levels of the ECG signal should also be examined. Furthermore, a combination of Huffman and delta coding is also worth exploring.

REFERENCES

Cervigón, R., McGinley, B., Craven, D., Glavin, M., and Jones, E. (2021). The Effects of Compression on the Detection of Atrial Fibrillation in ECG Signals. *Applied Sciences*, 11(13).

Chang, G. C. and Lin, Y. D. (2010). An Efficient Lossless ECG Compression Method Using Delta Coding and Optimal Selective Huffman Coding. In Lim, C. T. and Goh, J. C. H., editors, *6th World Congress of Biomechanics (WCB 2010). August 1-6, 2010 Singapore*, pages 1327–1330, Berlin, Heidelberg. Springer Berlin Heidelberg.

Elgendi, M., Mohamed, A., and Ward, R. (2017). Efficient ecg compression and qrs detection for e-health applications. *Scientific Reports*, 7.

Fang, H.-W. and Lu, C.-C. (2018). A real time and lossless encoding scheme for patch electrocardiogram monitors. *Applied Sciences*, 8(12).

Hatim, A., Latif, R., El Bachari, O., and Arioua, M. (2016). Efficient electrocardiogram (ECG) lossy compression scheme. In *2016 5th International Conference on Multimedia Computing and Systems (ICMCS)*, pages 151–156.

Jalaleddine, S., Hutchens, C., Strattan, R., and Coberly, W. (1990). ECG data compression techniques-a unified approach. *IEEE Transactions on Biomedical Engineering*, 37(4):329–343.

Mamaghanian, H., Khaled, N., Atienza, D., and Vandergheynst, P. (2011). Compressed sensing for real-time energy-efficient ecg compression on wireless body sensor nodes. *IEEE Transactions on Biomedical Engineering*, 58(9):2456–2466.

Němcová, A., Smisek, R., Maršánová, L., Smital, L., and Vitek, M. (2018). A comparative analysis of methods for evaluation of ECG signal quality after compression. *BioMed Research International*, 2018.

Rajoub, B. A. (2002). An efficient coding algorithm for the compression of ECG signals using the wavelet transform. *IEEE Transactions on Biomedical Engineering*, 49(4):355–362.

Ranjeet, K., Kumar, A., and Pandey, R. K. (2011). ECG signal compression using different techniques. In Unnikrishnan, S., Surve, S., and Bhoir, D., editors, *Advances in Computing, Communication and Control*, pages 231–241, Berlin, Heidelberg. Springer Berlin Heidelberg.

Rashkovska, A., Depolli, M., Tomašić, I., Avbelj, V., and Trobec, R. (2020). Medical-Grade ECG Sensor for Long-Term Monitoring. *Sensors*, 20(6):1695.

Trobec, R., Bregar, K., Depolli, M., and Mohorčič, M. (2018a). PCARD Wireless Protocol. Technical Report ISR2-PWP, Department of Communication Systems, Jožef Stefan Institute.

Trobec, R., Tomašić, I., Rashkovska, A., Depolli, M., and Avbelj, V. (2018b). *Body Sensors and Electrocardiography*. Springer.

Vilhar, A. and Depolli, M. (2018). Time synchronization problem in a multiple wireless ECG sensor measurement. In *14th Annual Conference on Wireless On-demand Network Systems and Services (WONS)*, pages 83–86.

Yildirim, O., Baloglu, U. B., Tan, R.-S., Ciaccio, E. J., and Acharya, U. R. (2019). A new approach for arrhythmia classification using deep coded features and lstm networks. *Computer Methods and Programs in Biomedicine*, 176:121–133.