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An alternative method of biomedical signal transmission through the GSM voice channel

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Abstract: In this work, a new solution for online and accurate biomedical data transmission is presented. For this purpose, a global system for mobile (GSM) communication voice channel is, for the first time, used as a communication link between the patient and healthcare provider. Biomedical signals are converted into speech-like signals before being transferred over a GSM voice channel. On the receiver side, speech-like symbols are stored in a symbols bank, and constructed using random stochastic signals. On the receiver end, the index of the symbol with the most similarity to the received signal is selected as the identified sample. This method enables us to communicate with an accuracy of 99.8% at a transfer rate of 110 samples per second and signal-to-noise ratio (SNR) of 10. By utilizing a GSM voice channel, any voice channel, such as a cell phone, can be used for data transmission. The transmitted signal is encoded; therefore, the connection is secured. GSM technology has benefits such as availability, reliability, and robustness. Additionally, GSM can be used as a backup or service for transmitting vital physiological signals in emergency situations (e.g. in an ambulance). This technology can also be used to transmit other physiological signals as well as nonphysiological generic data.

Key words: Electrocardiography, GSM, speech codecs, telemedicine, voice

1. Introduction

Different methods of sending critical patient data to monitoring centers and nursing stations have already been introduced. One of the most common methods of data exchange for this purpose is based on using the internet and associated general packet radio service (GPRS) channel [1–5]. In these methods, the signal is received through some protocols before being converted to the desired format. Then, it is received at the receiver end. Although using the GPRS channel eases the transmission (due to the simplicity of implementation), the internet connection stability on a mobile device varies with location, and disconnections from the internet may occur more often than a voice call. Another method to send the data in specified time intervals is via short message service (SMS) [4, 6–10]. However, SMS-based data transmission does not support any continuous connection and data are transmitted at some certain intervals [11]. The main disadvantage of this method is that the data is transmitted with semi-online connection.

This study indicates that transmission requirements can be satisfied by using a GSM voice channel and shows that this method of medical signal transmission over GSM voice channel is accurate enough and can be used as an alternative to the existing methods. The benefits of transmitting data through GSM voice channel have been explained in several studies [12–18]. However, none of these studies have used GSM voice channel

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for healthcare purposes. Using the voice channel of GSM makes the transmission channel more reachable and secure [13–15, 19]. This becomes especially important in emergency situations such as in an ambulance, where data transmission might be critical. Due to the properties of the GSM voice channel, direct signal transmission is not possible. Therefore, this study explains a method to overcome this problem.

The bandwidth of the data to transmit is limited due to the bandwidth of the GSM voice channel. Therefore, the transferred signal must be sampled at a frequency, i.e. 300 Hz, that falls within the limited range. Most of the bio-signals such as electrocardiogram (ECG), electrooculogram (EOG), photoplethysmogram (PPG), peripheral oxygen saturation (SpO2), and electroencephalogram (EEG) have the proper range of frequencies that meet the minimum requirements of the GSM channel. However, the model is not limited to biomedical signals only, and it could be used for other generic data as long as their bandwidths lie within the limits. ECG signal is one of the most common and vital biomedical signals, and with the continuous need for more accurate and secure methods of transmitting physiological signals and interest in telemedicine, this research would contribute as an alternative method to the existing technologies.

1.1. GSM voice channel properties and model

The properties of the GSM voice channel must be considered while dealing with any kind of data transmission over it. Anything that is transmitted over the GSM voice channel must maintain integrity against the GSM voice codec [20–22]. GSM voice codecs provide efficient transmission by compressing the speech signal and regenerating the signal at the other end. A GSM channel can support several codecs including full rate, enhanced full rate (EFR), adaptive multi-rate (AMR), and half rate codecs [21, 22]. In this paper, a GSM EFR codec was utilized for our GSM system. EFR is a GSM standard speech codec that was developed to improve the sound quality achieved by the GSM full rate codec with a bit rate of 12.2 kbps [21, 22]. The EFR compression technology is based upon closed loop code-excited linear prediction (CELP) coding [22, 23]. The CELP codec receives digitized speech sampled at 13 kHz and codes it in 20 ms frames.

In addition to maintaining integrity against the GSM codec, the ready-to-send signal must be recognized as speech by the voice activity detector [12]. The voice activity detector analyzes the input voice signal so that it only transmits the speech. If a coded speech-like message is not recognized as speech by the voice activity detector, the coded frame may be rejected and the system performance will be diminished. The block diagram of a closed-loop CELP is illustrated in Figure 1.

2. Materials and Methods

After sampling an ECG signal, each sample was assigned to a value within the range of 0 to $2^n - 1$, where n was the number of bits of the analog-to-digital converter (ADC). Each sample of the signal was converted into speech-like waveforms named as ‘symbols’. Symbols were sent over the GSM voice channel instead of the samples. For each value from 0 to $2^n - 1$, a corresponding symbol from S_0 to S_{2^n-1} was generated resulting in a total number of 2^n symbols (N_{sym}). Symbols were generated as time-domain series and stored in a *symbols bank*.

Sending the created sounds over the voice channel takes place after being passed through a codec, which modifies the input signal. Thus, the symbol bank should be generated such that symbol distortions become minimized during communication over the channel. At the receiver end, the received signal was compared with the symbols from the bank that was shared between the sender and the receiver. The symbol that had the highest similarity to the received signal was subsequently identified, and the index of this symbol was specified as the detected sample.

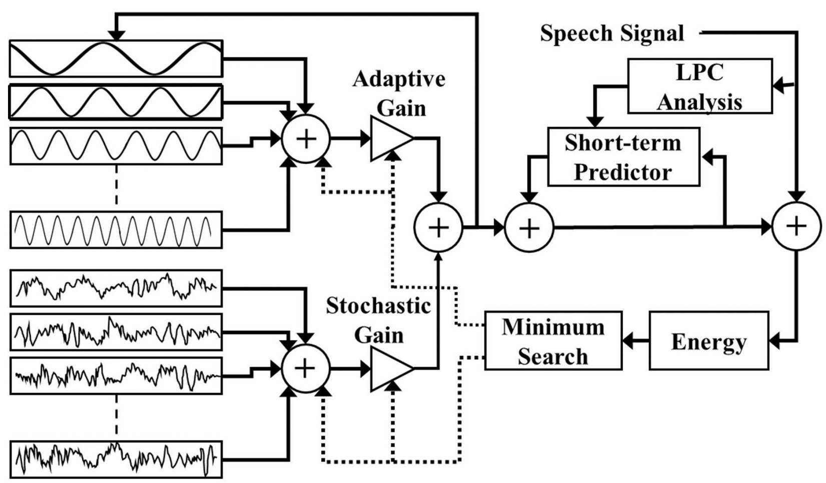

Figure 1. Closed-loop CELP codec [20].

Different methods can be used to quantify the similarity between the two signals including correlation, maximum a posteriori probability estimation, and dynamic time wrapping. In this study, a correlation function was utilized due to its simplicity of integration [24, 25]. So, the symbol with the highest correlation with the received signal was identified. Obviously, a higher degree of similarity between symbols (S_i) would result in a higher detection error, especially in the presence of high amplitude. Therefore, the length and waveform of symbols must be optimized to minimize the probability of identification error. The general structure of the system is illustrated in Figure 2.

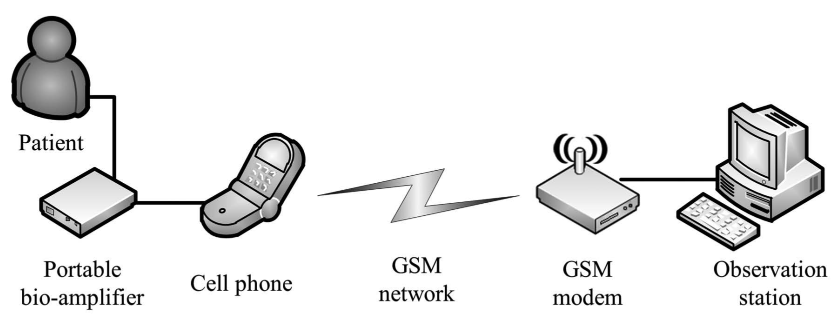

Figure 2. General system outline.

2.1. Data collection

A BioRadio (Great Lakes Neurotechnology, Cleveland, OH, USA) data acquisition unit was used to record the Lead-I ECG signal at a sampling frequency of 960 Hz and 16-bit ADC resolution. This setting collects clean and high-resolution signals. Subjects were seated on a chair and were asked to remain still during the test. The ECG signal was conditioned by setting the high and low cut-off frequencies at 0.05 Hz and 150 Hz, respectively.

2.2. Data mapping

For any input value of k, k^{th} speech-like symbol (c_k) in the bank was sent over the channel and at the receiver terminal, signal (u) is received:

$$System1 : c \;\rightarrow\; c_k, \tag{1}$$

$$System2 : u \;\rightarrow\; \hat{k}. \tag{2}$$

As shown in Figure 3, $\hat{k}$ is the detected value for k. Due to nonlinear properties of the GSM voice channel, received signal (c_k) is not exactly similar to the sent signal. So, statistical and probabilistic processes should be applied to identify k. Our solution was to compare each received signal to all of the stored symbols in the bank and to find the argument of the symbol with the highest similarity to the received signal:

$$\hat{k} = Arg(max[G(u_i,\ S_i)]), \tag{3}$$

where S_i is the i^{th} symbol in symbols bank, $\hat{k}$ is the estimated value of the transmitted value, k, and G is the similarity detection function.

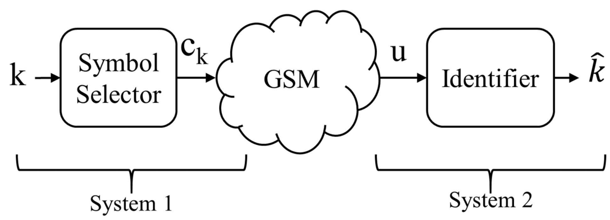

Figure 3. Data transmission structure.

After comparing the received signal with all previously stored symbols in the bank, the index of the symbols with the highest similarity to the received signal was identified as the detected sample.

For each received signal, we calculated the correlation value between the signal and all symbols as the indicator of similarity. The similarity detection function (G) previously mentioned in equation (3) can be described as:

$$G(x, y) = r_{x,y} = \frac{\sum_{j=1}^{l} x_j y_j - l(\bar{x}\bar{y})}{(l-1)s_x s_y}, \tag{4}$$

where $r_{x,y}$ represents the correlation value; s_x and s_y are standard deviations of x and y respectively and l represents the number of samples in x and y.

2.3. Generating symbols

Random signals with normal distribution have a wide frequency range with the least dependency on each other. In other words, the inner product of two random signals ($u[n]$ and $v[n]$) with normal distributions is zero:

$$\sum_{n=-\infty}^{\infty} u[n].v[n] = 0. \tag{5}$$

Using random signals would be ideal to use, but due to their wide frequency spectrum and un-similarity to the speech signal, random signals cannot be directly used as our symbols, even after passing them through band-pass filters. Instead, they can be used in an alternative symbol generating method. If a random signal is chosen as the frequency spectrum of a wave, then by applying an inverse discrete Fourier transform (IDFT), a band-limited random signal can be generated [15]. Equation (6) finds the inverse Fourier transform of the signal X[n] with the length of L:

$$IDFT(X[n]) = \frac{1}{N}\sum_{n=0}^{L-1} X[n].e^{i2\pi kn/L} = 0. \tag{6}$$

IDFT of a signal can contain both imaginary and real parts. To avoid having imaginary values in the transformed signal, the source signal must be odd in its imaginary and even in its real parts[15]:

$$C[n] = \left\{ \begin{array}{ll} R[n] + i.I[n] & ; n{>}0 \\ 0 & ; n{=}0 \\ R[-n]{-}\mathrm{i.I[n]} & ; n{<}0 \end{array} \right\}, \tag{7}$$

$$\left\{ \begin{array}{c} \mathrm{IDFT}\{C[n]\ \} = R_t[n_t] + i.I_T[n_t] \\ I_t[n_t] = 0 \end{array} \right\}, \tag{8}$$

where $C[n]$ represents the generated complex random wave, and $R[n]$ and $I[n]$ are real and imaginary parts of $C[n]$, respectively. $T[n]$ is the IDFT of $C[n]$ from spatial domain n into time domain n_t.

Assuming $T[n]$ as a side-band of the frequency spectrum of the symbol, by manipulating the values in $T[n]$, it is possible to modify the frequency parameters of $P[n]$.

A large number of initial symbols (N_t) were generated and stored in a temporary stack. The next step was to pass these symbols through a mathematical model of the GSM channel. When detection fails, both the transmitted and the incorrectly detected symbols were removed from the stack. These steps must be repeated until reaching to a zero incorrect detection rate. Based on n, 2^n symbols with the highest similarity to the associated received signal with the criteria of having at least 85% similarity and the lowest similarity to the other signalswere picked to construct the bank. The criterion of having similarity is a tradeoff between the symbol generating complexity and the accuracy of detection. In our method, having a correlation of at least 85% was chosen as the minimum requirement. If the number of approved symbols was not enough, new initial symbols would be added to the stack. The symbol selection process is explained in Algorithm (1).

Since the samples were nonlinearly encoded into symbols, and the channel also provides a nonlinear coding, the received signal is securely encrypted.

There were several parameters that can change the performance of the proposed system; i.e., by increasing the number of samples per symbol, the percentage of correctly identified symbols increases but the number of symbols per second decreases and vice versa. In other words, it was a trade-off between the transmission speed and detection accuracy.

Bandwidth limitations do not allow us to increase the sample reconstruction frequency. So, based on the properties of the channel, we needed to achieve optimum frequency, samples per symbol, and symbols per second values. Sample reconstruction frequency is related to the sampling frequency of a symbol; samples per symbol represents the number of samples in each symbol and is also equal to the symbol length, and symbols per second represent the transfer rate.

Algorithm 1: Symbol selection

```
Result: Find the least dependent symbols
N = N_t;
create N_t initial symbols;
for i := 1 to N do
    Ŝ_i = the i^th symbol passed through the model;
    for j := i+1 to N do
        if (corr(Ŝ_i, S_j) >= 0.85) then
            remove S_i from the bank;
            N_t = N_t - 1 ;
            break ;
        else
            (corr(Ŝ_i, S_j) < 0.85)
        end
        remove S_i from the bank;
        N_t = N_t - 1 ;
        break ;
    end
end
initialize corrMatrix_{1×N_t} ;
for i := 1 to N_t do
    for j := 1 to N_t do
        if (i ≠ j) then
            corrMatrix[i] = corrMatrix[i] + corr(S_i, S_j)/N_t ;
        end
    end
end
return the first 2^n symbols with the lowest average correlation ;
```

When the number of samples in the symbol decreases, statistical feature extraction can lead to false detection. On the other hand, by increasing the number of samples per second (N_{sam}), transfer rate decreases. So, we will have:

$$\alpha = \frac{SRR}{N_{sam}}, \tag{9}$$

where α indicates transmission transfer rate and SRR stands for sample reconstruction rate. Using greater transfer rate values provides a higher transmission speed but it also increases false detections. According to the selected transfer rate, the number of samples per symbol was calculated as represented in Table 1.

Due to the transmission frequency and Nyquist theorem, the digital raw input signal had to be downsampled to satisfy the maximum frequency range, using Equation (10).

$$D[m] = \frac{1}{n} \sum_{i=0}^{N-1} E[n-i].\delta[i]) \quad ; \quad m = Kn, \tag{10}$$

where K is a natural number, $E[n]$ is the original signal, $D[m]$ is the downsampled signal and $\delta[n]$ is the impulse function. The bandwidth of the signal can be reduced by employing equation (10).

Using low speeds may not be applicable to all signals. For example, the ECG signal covers the frequencies from 0.05 to 150 Hz and needs at least 300 Hz of sampling frequency that is equal to the transmission speed of 300 samples per second.

Table 1. Number of samples per symbol with different transfer rates (samples/second).

Transfer rate	N_{sam}
110	59
300	21
600	10
1200	5

3. Simulation results

To validate the system performance, a mathematical model of an EFR compression was implemented using MATLAB (Mathworks, MA, USA). All of the simulations were performed using a 64-bit Windows 10 with an Intel Xeon E5 CPU at 3.5 GHz and 32 GB of RAM. The ECG data was collected as explained in section 2.1 and this signal was transmitted using the proposed algorithm as described in section 2.2. First, a large number of individual symbols (N_t) were generated. After that, symbols were fed into the model (as illustrated in Figure 4) 10^3 times and all of the falsely detected symbols were removed from the bank.

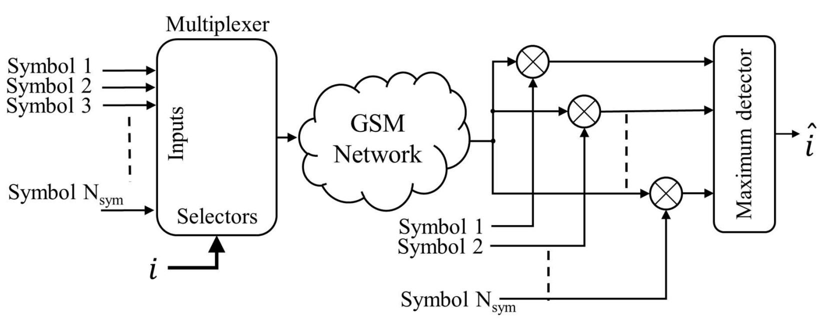

Figure 4. System model.

The performance of the detection method for different numbers of initial symbols is shown in Figure 5(a). The error rate is the percent of the incorrectly detected samples to all of the transmitted ECG samples.

To validate the performance of the system, a sample signal was used. A random generator was employed in MATLAB to generate noise and then the symbols were contaminated with different 4 levels of noise to produce the signal-to-noise ratios (SNR) of 1, 3, 6, and 10.

Since the first 2^{nbit} symbols are the best-fit symbols, they construct the symbols bank. Figure 5(b) shows the error rate for different values of SNR and N_{sam}; SNR values higher than three led to no detection error in our simulations.

Table 2 illustrates the performance of the system after running the model for 100 iterations at all of the possible transfer rates and different values of N_t and SNR; having a larger value of N_t improved the accuracy, and higher transmission speed increased misdetections. The effect of low SNR is more distinguishable in transmissions at higher speeds but larger N_t can significantly compensate for it.

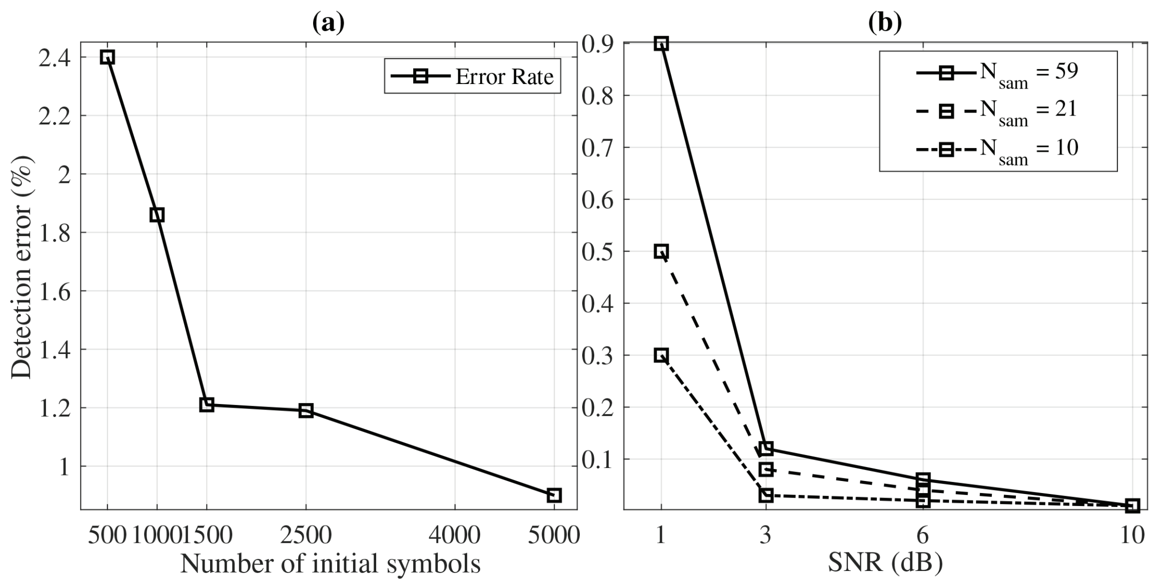

Figure 5. Error rate for various numbers of initial symbols transfer rate= 110 *samplespersecond* (a); and for different values of SNR and N_{sam} (b).

Table 2. Number of samples per symbol in different transfer rates.

Transfer rate (samples per second)	N_{sam}	N_t	SNR(dB)	Accuracy (%)
110	59	10000	10	99.8
110	59	5000	10	99.3
110	59	2500	10	98.7
110	59	10000	3	99.2
110	59	5000	3	98.5
110	59	2500	3	95.0
300	21	10000	10	98.2
300	21	5000	10	94.7
300	21	2500	10	94.1
300	21	10000	3	93.2
300	21	5000	3	89.7
300	21	2500	3	82.2
600	10	10000	10	97.0
600	10	5000	10	90.8
600	10	2500	10	88.1
600	10	10000	3	96.1
600	10	5000	3	85.2
600	10	2500	3	77.6

4. Discussion and conclusion

Providing a secure and stable vital signal transmission method becomes challenging when the data channel is either unstable or unavailable.

This paper proposes an alternative approach to the existing methods (such as the use of SMS, ZigBee, Wi-Fi, RF) and uses a GSM voice channel, which is usually more accessible and has more beam coverage. An ECG signal was transferred over a GSM channel to evaluate the performance using a computer model.

The proposed method is based on converting each sample of the recorded signal into a speech-like waveform named as *symbols*. Symbols are highly uncorrelated in such a way that at the receiver side the symbol having the highest correlation with the received signal is detected and the corresponding index of the detected symbol is identified as the received sample. The number of symbols in symbols bank depends on the number of bits in each sample. 2^{nbit} symbols are needed to construct the bank for samples digitalized by a $nbit$ ADC.

10^4 initial symbols were constructed after generating a random signal, zero-padding and employing an IDFT, as explained in section 2. Then, 2^{nbit} symbols with the lowest similarity were stored in the bank. The length of each symbol (N_{sam}) is limited to the transmission speed, as described in (9).

As listed in Table (2), having a larger number of initial symbols can decrease the detection error rate. Since the symbols are generated and stored for once, having the highest possible number of N_t can improve the performance. Moreover, increasing the transfer rate directly increases the overall error rate. Therefore, there is a trade-off between speed and low detection error rate. To have a safe and trustable link, it is recommended to transmit the signals with narrower bandwidth at lower speeds and use the higher speeds only if it is necessary. This table also indicated that having a large number of initial symbols and lower speeds could decrease the effect of low SNR.

A similar form of this technique has been used in three studies [12, 15, 18]. However, the symbol generation approach of our study is different. None of the previous studies has used this technique in transmitting biomedical signals. In one of the previously conducted studies [15], symbol generation was based on a genetic algorithm in such a way that the initial symbols were improved by applying mutations and cross-overs on a certain number of symbols and the best population was generated. Their method includes modifying the symbols (*alphabets*) by finding the value of an objective function from their spatial values and manipulating them to lower the cost function in a recursive optimization loop. In contrast, our study uses a more practical approach by using a very large group of initial symbols and eliminating the statistically similar ones. In other words, our method consumes more time to generate the symbols but since it deals with a very large set of initial symbols, the results showed a better performance than the other studies.

In a previous study, a digital modulation method based on an autoregressive model of speech was proposed [18]. The reported bit error rates for bits per second (bps) speeds of 500 and 522 were 38.94% and 44.12% respectively while our method showed only 3% misdetections at 600 bps.

In another study, symbols were generated using three parameters: line spectrum frequencies (LSF), pitch, and energy index of the input signal [12]. The main difference between our study and the mentioned one is the nature of the input signal. The transmitted signal in our study is an ECG where the ECG signal is converted into a speech-like signal for transmission while in the mentioned study a regular speech signal was transmitted.

Since every transmission is somehow encoded with speech-like signals, it is only meaningful for the receivers that obtain the symbols bank and wiretappers will only receive an encoded sound that is not possible to be translated. Therefore, this transmission strategy provides a secure channel between the sender and the receiver.

Within the existing methods to quantify the similarity between two signals such as correlation, maximum a posteriori probability estimation, and dynamic time wrapping, a correlation function was preferred in this study due to its simplicity of integration.

To demonstrate the accuracy of our model, a recorded ECG signal was used. As seen in Figure 6, the sent and received signals were almost identical.

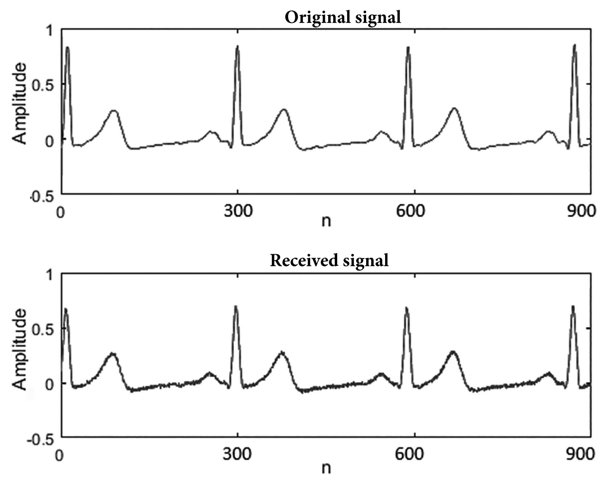

Figure 6. Sent signal (Top); System's output (Bottom), at a transfer rate of 300 samples per second & SNR of 10.

Although biomedical signals such as ECG, EOG, EEG, SpO2, body temperature, etc., can be transmitted with this method, one of the limitations of this study is in sending wide-bandwidths signals. For example, electromyography signals cannot be transmitted with this method. However, this method is not limited to biomedical data and can also be used to transmit non-physiological generic data.

Finally, this technique can be used in absence of data channel coverage or even as a backup plan to existing strategies in mobile communication methods such as ambulances or outdoor environments.

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