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Efficient Real-Time Lossless EMG Data Transmission to Monitor Pre-Term Delivery in a Medical Information System

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Abstract: An estimated 15 million babies are born prematurely every year worldwide, and suffer from disabilities. Appropriate care of these pre-term babies immediately after birth through telemedicine monitoring is vital. However, problems associated with a limited bandwidth and network overload due to the excessive size of the electromyography (EMG) signal impede the practical application of such medical information systems. Therefore, this research proposes an EMG uterine monitoring transmission solution (EUMTS), a lossless efficient real-time EMG transmission solution that solves such problems through efficient EMG data lossless compression. EMG data samples obtained from the Physionet PhysioBank database were used. Solution performance comparisons were conducted using Lempel-Ziv Welch (LZW) and Huffman methods, in addition to related researches. The LZW and Huffman methods showed *CRs* of 1.87 and 1.90, respectively, compared to 3.61 for the proposed algorithm. This was relatively high compared to related researches, even when considering that those researches were lossy whereas the proposed research was lossless. The results also showed that the proposed algorithm contributes to a reduction in battery consumption by reducing the wake-up time by 1470.6 ms. Therefore, EUMTS will contribute to providing an efficient wireless transmission environment for the prediction of pre-term delivery, enabling immediate interventions by medical professionals. Another novel point of EUMTS is that it is a lossless algorithm, which will prevent any misjudgement by clinicians because the data will not be distorted. Pre-term babies may receive point-of-care immediately after birth, preventing exposure to the development of disabilities.

Keywords: compression; EMG; lossless; medical information system; pre-term birth; telemedicine; wireless

1. Introduction

An estimated 15 million babies are born prematurely (pre-term birth) every year worldwide, which is more than one in ten [1]. The World Health Organization (WHO) has indicated that almost one million children die annually, due to complications associated with pre-term birth. Even if the babies survive, they are likely to face a lifetime of disability (learning disabilities, visual disabilities, hearing problems, etc.), which is difficult to resolve using medical treatment.

Globally, prematurity is the leading cause of death in children under the age of five years. The fact that preterm birth rates are increasing in almost all countries is disturbing [2]. There is a growing need for a solution to this problem, as the prevention of pre-term birth is extremely difficult because it is both spontaneous and unpredictable.

One feasible solution, also strongly recommended by WHO, is to provide essential care at the "Golden Time" during the postnatal period. The administration of antibiotics during this time could prevent infections developing in newborns. The appropriate timing for this can be guaranteed using information technology (IT) [3]. By combining health services and IT, uterine parameters can be monitored for signs of pre-term symptoms.

Recent studies of a uterine electromyography (EMG) signal focused on the prediction or detection of pre-term birth [4,5]. These technologies facilitate the remote monitoring of preterm incidents. Furthermore, a hardware feature exists to support such preterm monitoring. A solution [6] issued by Principe proposed a preterm monitoring system and method that monitors the EMG signals of the pregnant mother.

However, the problem of the current features of these platforms is that, due to the massive size of the EMG signal [7], the network bandwidth is constantly overloaded. Hardware and software that support EMG transmission are also overwhelmed, because it is recommended that maternal patients are monitored for 40 weeks (at least 12 weeks) during the gestational period. This results in problems such as rapid battery consumption and overheating. To solve this, compression of the transmitted data is required. This would allow more patients to be supported using a limited bandwidth [8], resulting in a safe EMG signal transmission environment for transmitting maternal patient's signal.

Another problem regarding the transmission of EMG signals is data loss in wireless transmission. There are two cases of data loss; one is natural error, and the other is the loss that occurs from lossy transmission techniques. If data is compressed, it can be transmitted as fast as possible and can be rapidly recovered. However, it is equally important to apply lossless techniques because an EMG signal is a vital sign of the patient's state, and any distortion resulting from data loss may critically affect clinicians' decisions.

Accordingly, this research proposes a real-time wireless lossless EMG data transmission solution termed an EMG uterine monitoring transmission solution (EUMTS), to support the systems for monitoring pregnant women for early symptoms of pre-term labor. Our prior research algorithm regarding an electrocardiography (ECG) was modified and applied to EMG signals, which yielded a high performance result. The significant point of this is that EMG signal compression performance has been lower than expected in other researches thus far, because of its extreme irregularity, and was rarely touched. The proposed research handled this field and produced comparatively high results, even without any data loss. The proposed solution is envisioned to contribute to providing a seamless network platform for preterm telemedicine, facilitating the appropriate care of pre-term babies prior to exposure to infection and contamination. This is a unique contribution.

2. Related Works

2.1. Preterm Prevention Monitoring System

As mentioned earlier, Principe et al. [6] proposed the electrohysterogram (EHG, uterine EMG) monitoring system for sensing the EMG signals of the mother and sending them to the health device through wireless communication. The key specific features are depicted in Figure 1, which is taken from Principe's patent [6].

A surface sensor, which comprises multiple leads, is attached to the uterine surface of the mother (Figures 1a–d and 3a,b). Sensed signals are then sent through the wired network (shown as analog-to-digital convertible shielded cables 4 and 5 in Figure 1) or through a wireless network to the personal health device (shown as 6 in Figure 1), to spatially depict the contraction status (shown as 7 in Figure 1) in real-time. The proposed solution in this study was developed to support the seamless networking of such EMG information monitoring systems, which will be specifically presented in Section 3.

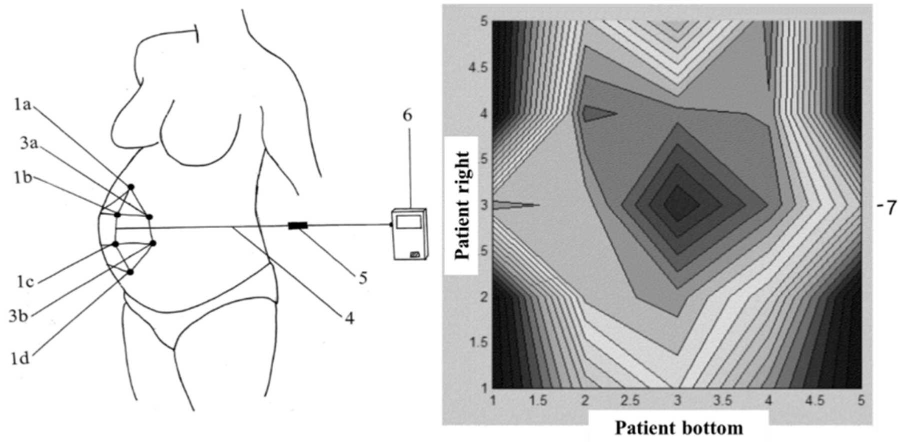

Figure 1. Principe's system and method for analyzing the progress of labor and preterm labor.

2.2. Limited Bandwidth in Practical Real-Time Wireless Communication and Insufficient Battery Life in Pre-Term Monitoring

When using 12 channels, a 32-bit resolution, and a 20 Hz EMG monitoring environment, approximately 7.6 Kbps of bandwidth is required. Considering Bluetooth 4.2. (recent version of Bluetooth), its Low Energy (BLE) specifications are appropriate for monitoring situations, mainly because of its low energy consumption. BLE's throughput specification supports up to 7 Kbps [9]. This is a huge lack of network bandwidth because, realistically, 100% of the 7 Kbps cannot be allocated to EMG channels alone. Headers, security, error correction, and other kinds of data (maybe even other signals than EMG) inevitably take up a considerable portion, even when 100% of the portion alone is not enough for the EMG transmission itself.

Furthermore, in wireless sensor networks, sensors are continuously strained in order to support a seamless network. Engineers are constantly working to increase the run-time of such battery-powered devices [10], because their seamless connection is especially important in smart healthcare networks. However, the need for EMG transmission and a long monitoring length are still large barriers for wireless communications in pre-term monitoring.

It is optimal for a maternal EMG to be monitored for 40 full weeks during the gestation period. At least the 12 weeks (=40 weeks of full period 28 weeks of extremely pre-term period, refer to Section 2.4) before birth should be monitored in real-time, in order to react within the "Golden time". Considering 12 channels, a 32-bit resolution, and a 20 Hz transmission network environment, a minimum of approximately 6.9 Giga Bytes (GB) to a maximum of 23.2 GB of data must be transferred or stored per patient of maternity.

This is affected by the number of maternity patients supported, meaning that an immense amount of data must be transferred and stored for long periods. In reality, this is a great overload to any wireless transmission situation, both to the device and the network.

Therefore, this overloaded environment is practically impossible to support. Heavy battery consumption near wireless networks such as Bluetooth or Wi-Fi suffer from network shortages. Large quantities of EMG data take longer to transmit, and monitoring the pre-term status requires lengthy monitoring periods, resulting in immense battery consumption. If the data size can be reduced, wireless transmission network overload will be lowered and the battery life-span will be increased.

We proposed an algorithm solution to transmit data in a compact size in real-time, thereby contributing to lessening the strains in the wireless communication bandwidth and data transmission strains in battery consumption.

2.3. Prior Research on Term & Pre-Term EMG Signals

Searching the Web of Science (WoS) yielded little research regarding term and pre-term EMG signals. Most researches were concentrated on the monitoring and prediction of preterm birth [11,12], with some focusing on the maternal health system itself. Few other studies were related to the classification of term or pre-term [13] EMG signals for the prediction and detection of preterm birth.

Due to the scarcity of research into the compression of EMG signals of maternal patients, studies of EMG signals, regardless of disease type, were used for comparison (refer to Section 4.2). The studies by Balouchestani [14], Itiki [15], Norris [16], Berger [17], Filho [18], and Trabuco [7] were selected. Specific summary details of the selected researches are shown in Table 1.

Table 1. Selected prior studies.

Study	Notes
Balouchestani [14]	Batch processing algorithm based on analog-compressed sensing (CS) for the receiver side of an ultra-low-power wearable and wireless surface EMG (sEMG) sensor.
Itiki [15]	Compression of high definition (HD) EMG signals recorded by two-dimensional electrode matrices at different muscle-contraction forces. Also includes methodological aspects of compressing HD EMG signals of the non-pinnate (upper trapezius) and pinnate (medial gastrocnemius) muscles using image compression techniques. No real-time supportability.
Norris [16]	Algorithm based on an embedded zero-tree wavelets (EZW) scheme. Does not support real-time.
Berger [17]	Compression algorithm based on wavelet transform, neural network bit allocation procedure and arithmetic entropy coding. Does not support real-time.
Filho [18]	Batch processing algorithm based on a recurrent pattern algorithm.
Trabuco [7]	Algorithm based on discrete wavelet transform for spectral decomposition and de-correlation. Does not support real-time.

The proposed algorithm was not compared to other types of signals, because signals other than EMG have different and unique characteristics. For example, ECG is much regular than that of EMG, so the same optimization technology cannot be applied. In conclusion, in order to objectively evaluate the performance of the proposed algorithm (which is optimized for EMG), comparisons of the same EMG signal-related algorithms should be made. This is also the same case for the prior related researches regarding EMG compression selected above, which also chose to compare similar signal data.

2.4. Term-Preterm Birth

The normal human gestation period is 40 weeks. However, labor prior to the end of the 37th week is known as premature (pre-term) labor, which is abnormal [19]. Pre-term births are classified as shown in Table 2.

Table 2. Classification of Pre-term Birth Based on the Gestational Period.

Sub-Category	Gestational Period
Extremely pre-term	Less than 28 weeks
Very pre-term	28 to 32 weeks
Moderate to late pre-term	32 to less than 37 weeks

Pre-term birth usually leads to unexpected illness, injuries, or disorders that may last a lifetime. Therefore, it is strongly recommended that induction or a caesarean birth is not planned or implemented before 39 weeks [20].

2.5. Digital Signal Compression and EMG

The application of digital signal compression has been practiced in our prior researches [21–23]. An appropriate analysis of digital signal redundancy enables the development of a powerful compression algorithm, and an effective compression ratio.

In this study, compression of the EMG signal of maternal patients was attempted. The EMG signal is generally produced by skeletal muscles and can be used to detect medical abnormalities. Figure 2 shows an example EMG signal of one of the signals used in this study.

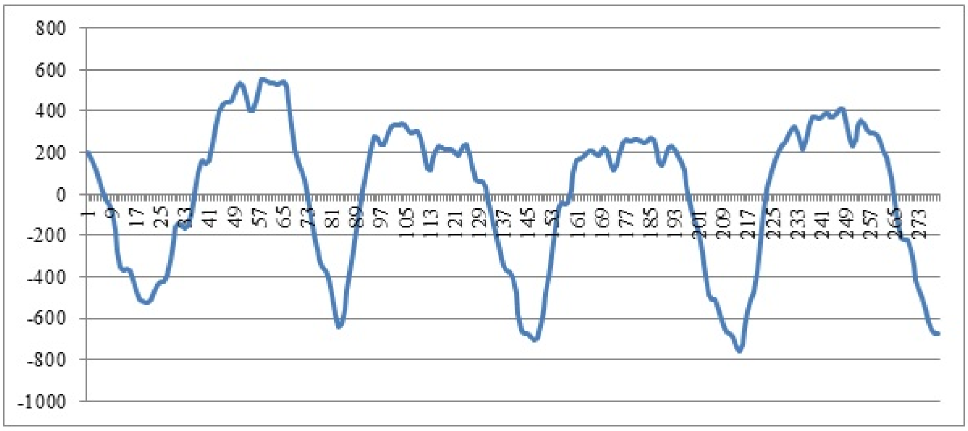

Figure 2. Example EMG signal interval.

There are limitations in efficiently compressing EMG signals because they contain a lower redundancy due to their irregularity (Figure 2). For example, ECG signals contain a very high redundancy due to their distinctive periodical cycles (PQRST interval). Efficient lossless ECG compression in a real-time medical information system environment has been proposed [8], but in this study, a different approach was needed. EMG data had to be analyzed more thoroughly due to its extreme irregularity (low redundancy) compared to ECG (high redundancy). A different compression algorithm was applied, and the main modification was analyzing and developing a different dictionary code word optimized for EMG. The specific features of the algorithm proposed in this research are described in Section 3.2.

3. System Description

3.1. Overall System Architecture

The overall system architecture of a typical term and pre-term monitoring system [24] for mothers is discussed in this Section. The system is depicted in Figure 3.

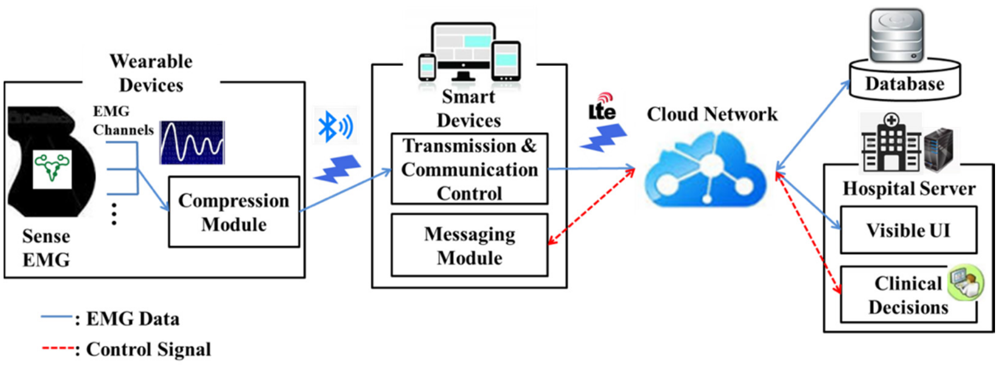

Figure 3. Architecture of a pre-term monitoring system.

Wearable sensors are unobtrusively attached to the patient; these detect the EMG signals, which contain indicators of the term/pre-term condition. Raw EMG data (straight lines) obtained from the sensors in each channel are transmitted to the wearable device (e.g., wearable watch), where they are encoded to be efficiently transmitted through our proposed compression module. The algorithm developed for the compression module is described in Section 3.2.

The compressed EMG signal is sent to the smart device, which contains the transmission direction and communication control module. The network environment used here is usually BLE. The Transmission & Communication module decides where the signals or messages should be sent. If the EMG signal shows no signs of pre-term delivery, it is sent to the database via the cloud network. In this case, the used network may be 4 G (LTE). If the EMG signal shows signs of pre-term delivery, it is sent to the hospital server.

In the hospital server, the visual User Interface (UI) module decodes the compressed EMG data into a user-friendly format, and presents it to the clinician. Clinical decisions or feedbacks are then sent to the smart device (message and control communications are depicted as dotted lines in Figure 3). Finally, the potential patient may receive clinical prevention services through the smart device UI; for example, warning of the risk of pre-term delivery. This facilitates screening for prematurity, allowing precautions to be taken; for example, appropriate interventions after premature birth, preventing the development of complex illness [25] due to a pre-term birth.

An important note that should not be confused is that in the telemonitoring situations for maternal patients shown in Figure 3, real-time interaction is not implemented between the healthcare professional and patient. Physicians are only alerted by the system when abnormality is detected, and vice versa, and they only provide feedback to patients when necessary. Real-time communication is only applied between wearable devices and smart devices (BLE transmission).

3.2. Compression Algorithm

This study developed a compression algorithm for the lossless real-time transmission of the EMG signals of mothers. The mainstream algorithm model of our prior research regarding ECG [8] was used, but its core dictionary code word was modified for the application to EMG signals. The algorithm was designed to be spread throughout the proposed system architecture, contributing to a seamless and lossless transmission network environment. The emphasis on the lossless nature of the system is an important feature, since the network environment proposed in this system handles potentially critical medical information. Any loss in signal may lead to clinical misjudgment or diagnostic errors. A flow chart of the EMG transmission solution is shown in Figure 4.

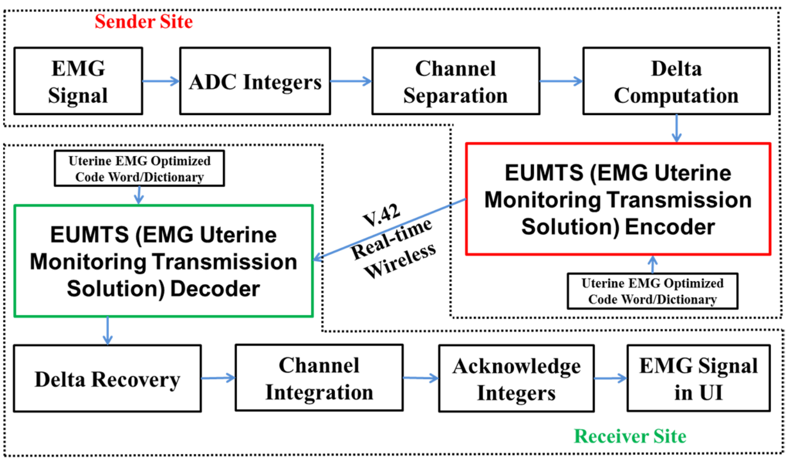

Figure 4. Functional diagram of the proposed system.

The EMG data are first obtained and converted to integers. Channels are then separated according to each EMG lead. Then, delta computation of the samples in each lead is implemented.

Variable bits are dynamically and appropriately allocated for each sample, according to the code word size. Note that the EMG samples originally have 32 bits (EMG machines collect samples in

4 bytes by default). An example histogram regarding the distribution curve of dynamic EMG records after delta computation is shown in Figure 5. An example record was randomly selected from those used in this study.

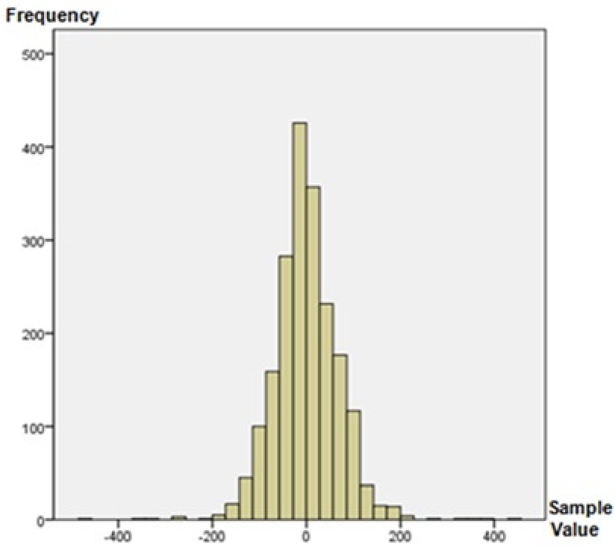

Figure 5. Distribution curve of example records after delta computation.

In Table 3, bit allocation is calculated from the selected example distributions shown in Figure 5. 8 bits (1 byte) were allocated to sample integers from −128 to 127, which were originally 32 bits, and 16 bits (2 bytes) were allocated to sample integers from −32,768 to −129 or from 128 to 32,767, which were also originally 32 bits.

Table 3. Frequency of Samples Allocated to 1 and 2 Bytes.

Size	Frequency	Percentage
1 byte	1904	95.2
2 bytes	96	4.8

EUMTS is then applied as the final process of the compression algorithm, creating the final compressed EMG data. Bit allocation and code word modification are the core processes of the EUMTS, and the main difference compared to our prior research [8]. As mentioned in Section 2.3, EMG data have a low redundancy (Table 4). Of the total of 2000 samples, 638 (31.4%) were redundant. Thus, the sample diversity was 1372 (based on Figure 5 and Table 3); therefore, a different code length compared to in cases of high redundancy was needed, not to mention a different dictionary. The proposed algorithm was modified accordingly, and was optimized for the characteristics of EMG signals.

Table 4. Low Redundancy in EMG Signals.

Classification	Frequency	Percentage
Redundant samples	628	31.4
Sample diversity	1372	68.6
Total	2000	100

Efficiently compressed data by EUMTS (lossless) is then transferred by real-time wireless transmission. At the receiver site, the decoding process is the opposite. EUMTS decodes the compressed signal based on a uterine EMG optimized code word/dictionary, delta computed values are recovered, and channels are integrated. Finally, integers are acknowledged and the receiver end users (usually clinicians) check the EMG signal in user interface form.

3.3. Specifications for Real-Time Wireless Transmission

The EUMTS was based on V.42 bis [26]. This is because V.42 bis functions as a wireless transmission environment for real-time compressing and sending data for dictionary-based Lempel-Ziv Welch (LZW) variant methods, enabling the proposed solution to transmit data in real-time packet units. In other words, the proposed algorithm is not a static method that saves, compresses, and transmits EMG signals. The proposed algorithm dynamically compresses and sends real-time EMG signals by data packets. The main specifications of V.42 bis are shown in Figure 6.

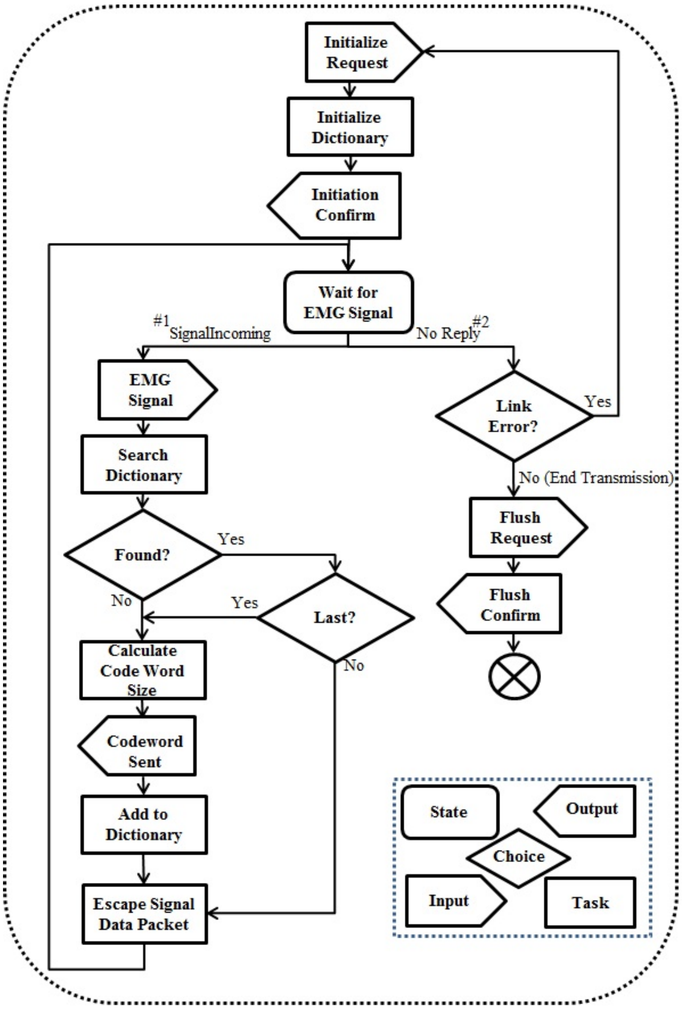

Figure 6. Flow chart specifications of compressing & transmitting real-time data of EUMTS.

After initiating a request and confirming that initiation, the algorithm processes dictionary codes by EMG signal data packets. In scenario #1, the code word and dictionary are calculated, as long as there are incoming signals transmitted in data packets. If the signal sample is not found in the dictionary, it calculates a new code word size, and adds it to the dictionary. The end procedure always matches the newly initialized string signal sequence, so that strings are matched real-time. If the signal sample is found in the dictionary, there is no need for further dictionary addition, so it escapes and waits for another signal sequence. This way, the EMG signal dictionary is trained in real-time through our proposed algorithm. There is no need for delays deriving from statically saving and compressing.

If there is no reply in the incoming character, check first if it's due to a link error. If an error has occurred, re-initiate the request. If it is not an error and it is the end of transmission, request and confirm the flush and end algorithm. The main role of the flush function is to meet the needs of the real-time dynamic bit allocation transmission of LZW. If an error occurs and an empty bit occurs, the flush function fills the empty bit with 0 integer values. Constructed on the real-time specifications of V.42 bis, the proposed algorithm supports dynamic real-time transmission in packet units. In the evaluation Section, the compression performance of the developed algorithm is evaluated.

4. Results

4.1. Materials and Methods

EMG data samples were obtained from the Physionet PhysioBank database [27]. Among the signal databases provided by Physionet, the Term-Preterm EHG Database (TPEHG DB,) was used. According to Physionet, the data were obtained at the Department of Obstetrics and Gynecology of the University Medical Centre, Ljubljana.

The TPEHG DB contains 300 uterine EMG records from 300 pregnant women. Each record consisted of 12 EMG channels, and the sampling frequency was 20 Hz (sampling interval of 0.05 s). In this evaluation, 30 records were randomly chosen for evaluation, each with a length of 2000 samples. As mentioned in Section 3.2, each sample had a resolution of 32 bits.

Solution performance comparisons were conducted for widely used algorithms (LZW, Huffman), and then for related researches. Statistical analysis was conducted using SPSS ver. 23 (IBM, New York, NY, USA). The C programming language was used for algorithm programming, development, and evaluation, with Microsoft Visual Studio 2016 (Microsoft, New York, NY, USA).

4.2. Compression Ratio Results

To evaluate the compression performance of the proposed algorithm, the LZW [28,29] and Huffman [30] algorithms, the most widely used compression algorithms, were first used for comparison. The compression ratio (*CR*) was calculated using the following Equation (1), where *US* is the uncompressed size and *CS* is the compressed size:

$$CR = US/CS \tag{1}$$

A comparison of the *CR* with those of other widely used algorithms is shown in Table 5. LZW and Huffman showed *CRs* of 1.87 and 1.90, respectively, compared to 3.61 for the proposed algorithm, thus exhibiting a significant difference. Therefore, the proposed algorithm yielded a more efficient compression.

Table 5. Comparison of *CR* with those of other algorithms.

CR Values	LZW	Huffman	Proposed Algorithm
Average ± Standard Deviation	1.87 ± 0.03	1.90 ± 0.01	3.61 ± 0.01

For a further subjective evaluation of the performance of the proposed algorithm, a comparison with prior studies was conducted. Few studies of lossless compression of EMG signals of maternal subjects are extant, but recent researches similar to this study were used. Note that the percentage residual difference (*PRD*) is calculated according to Equation (2).

$$PRD = \sqrt{\frac{\sum_{n=0}^{K-1}(x[n] - \hat{x}[n])^2}{\sum_{n=0}^{K-1} x^2[n]}} \times 100\% \tag{2}$$

In Equation (2), x is the uncompressed original signal and $\hat{x}$ is the reconstructed signal after compression. In addition, K is the total sample length of the signal. For instance, the length of K is 2000 in the proposed experiment. A comparison of the *PRD* and *CR* of the proposed algorithm and previous researches is shown in Table 6.

Table 6. Comparison of *CR* with related researches.

Related Researches	PRD	CR	Lossy/Lossless	Real-Time
Balouchestani [14]	0.10	2.00	Lossy	Not Able
Itiki [15]	0.00	1.69	Lossless	Not Able
Norris [16]	3.90	3.33	Lossy	Not Able
Berger [17]	1.79	3.33	Lossy	Not Able
Filho [18]	1.21	3.33	Lossy	Not Able
Trabuco [7]	2.12	3.33	Lossy	Not Able
Proposed algorithm	0.00	3.61	Lossless	Able

For an objective comparison, a *CR* under similar circumstances to *PRD* was compared, because the proposed algorithm was lossy (*PRD* of 0). The lower the *PRD*, the lower the loss rate. Balouchestani reported a *CR* of 2.00, and Itiki a *CR* of 1.69. Norris, Berger, Filho, and Trabuco reported *CRs* of 3.33, but different *PRD* values. The *PRD* values of Norris, Berger, Filho, and Trabuco were 3.90, 1.79, 1.21, and 2.12, respectively.

The proposed algorithm was more efficient (*CR*, 3.61) than those in previous studies. Additionally, Balouchestani, Norris, Berger, Filho, and Trabuco had markedly higher *PRD* values than the proposed algorithm. Although not proposed in their research, their compression performances will be far lower in close-to-zero *PRD* situations.

4.3. Execution Time Difference Results

Basically, microcontrollers are in a 'wake-up' state when processing or transmitting data, and are in a 'sleep' state when not. The duration of time during which the microcontroller is in a 'wake-up' state is when it consumes its battery.

The algorithm contributes to reducing the battery consumption by reducing the packet size of transmitted data, because the transmitting data time is reduced. However, battery consumption not only depends on the transmission time (transmission time needed per packet, *tt*), but also on the processor load (processing time needed per packet, *pt*). The higher the processor load, the higher the consumption, because the processing time (wake-up time) is increased. Since the algorithm increases the processor load, there is some trade-off between transmission time and processing time. Therefore, an assessment of the complex algorithm's contribution to the overall effect in computing time (total computing operations time per packet, *ct*) is needed, and is thus evaluated in this section. The relation between *pt*, *tt*, and *ct* follows Equation (3), and is shown in an example situation in Figure 7.

$$\begin{cases} ct = pt\ (if\ pt > tt) \\ ct = tt\ (if\ pt < tt) \end{cases} \tag{3}$$

Two conditions A and B must be compared for an evaluation of the algorithm's effect on *ct*. A is the time per packet needed to process and transmit data packets using the original system, and B is the time per packet needed to process and transmit data packets using the algorithm that is applied to the original system. The specific steps used to assess A and B are depicted in Figure 8.

To assess the *ct* of A, first set the timer on, input the EMG data, packetize for transmission, transmit the data packets, unpacketize the data, output the EMG data, and set the timer off. On the other hand, to assess the *ct* of B, also set the timer on, input the EMG data, compress the data using EUMTS, packetize for transmission, transmit the data packets, unpacketize the data, uncompress the data using an EUMTS decoder, output the EMG data, and set the timer off. Note that the packet size used in this experiment is 20 samples, because Bluetooth usually sends one packet per second, and because the database used here is 20 Hz. Results of the A and B time comparison in milliseconds are shown in Table 7.

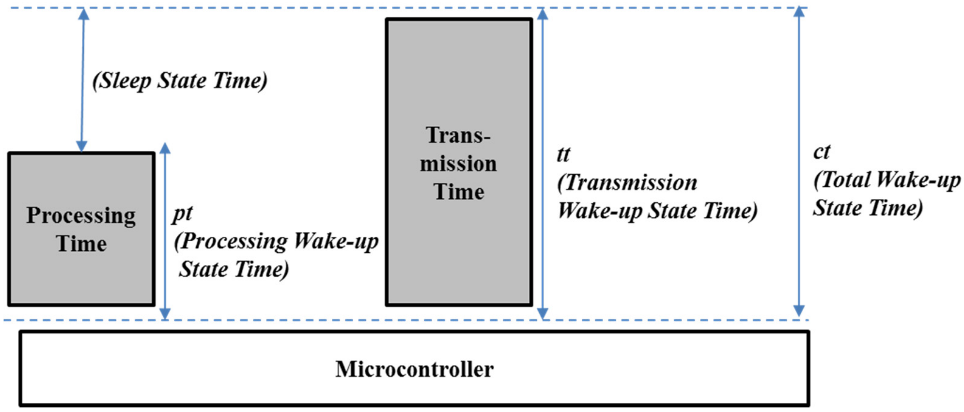

Figure 7. Example relation between *pt*, *tt*, and *ct* when *tt* is longer than *pt*.

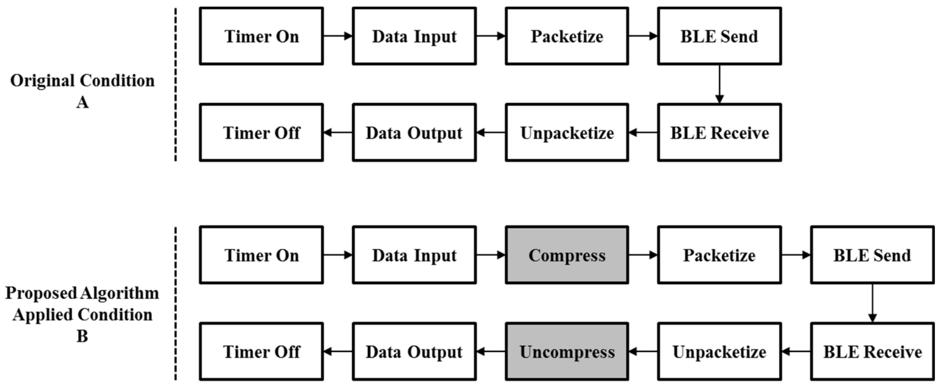

Figure 8. Comparison between original process and proposed algorithm applied process.

Table 7. Operation Second Per Packet Comparison between A and B (Milliseconds, ms).

Conditions	*pt*	*tt*	*ct*
A	2.0 ms	2340.6 ms	2340.6 ms
B	870.0 ms	648.4 ms	870.0 ms

The processor used for evaluation was a recent updated version of microcontroller 8051 that is suitable for wearable operating systems. The network environment was Bluetooth 4.2 Low Energy. Using the database mentioned in Section 4.1, 12 channels of EMG data containing 1000 packets (20,000 samples) in each channel were used in this experiment (size approximately 2 MB).

The results showed that, naturally, the complexity of the proposed algorithm increased the processing time needed per packet from 2.0 ms to 870.0 ms (*pt*). However, EUMTS contributed to the largely decreasing transmission time needed per packet from 2340.6 ms to 648.4 ms, by efficiently compressing the data packet size (*tt*). In conclusion, in spite of a trade-off between the processing time and transmission time, the overall computation time decreased from 2340.6 ms to 870.0 ms (*ct*), thereby contributing to reducing the battery consumption of microcontrollers. In other words, by using the proposed algorithm, the total wake-up state needed in order to process and transmit data decreased for the 8051 microcontroller.

5. Discussion and Conclusions

This research proposed EUMTS, a seamless, lossless real-time transmission solution for the monitoring of preterm birth. A previously published algorithm was modified and applied to uterine EMG signals and optimized for uterine EMG. The developed algorithm had a higher *CR* and lower *PRD* than other widely used algorithms and those proposed by others.

A higher compression digital signal ratio is important, especially for screening for pre-term birth. Without compression, the massive size of the EMG data overloads the network, resulting in network outages and a high battery-power consumption. The results in this proposed research showed that the proposed algorithm contributes to a reduction in battery consumption by reducing the wake-up time by 1470.6 ms. A unique compression technique has additional external affects such as network security and preventing privacy issues [31], blocking any trespassers trying to interrupt the medical system network.

Using the proposed algorithm, maternal EMG signals can be transmitted seamlessly through telemedicine networks. Signals can be compressed with a high efficiency, with more data being transmitted at a higher speed under limited bandwidth situations [32]. Also, the data recovery time is reduced, even if errors occur.

Moreover, digital EMG signals are important indicators of maternal health, and any data loss leads to the possibility of clinical decision errors. The solution proposed in this study is a lossless transmission solution, and is appropriate for EMG signals because EMG signals are precious indicators and information of patients.

The proposed study is also a real-time supporting transmission solution, which is especially fit for telemedicine systems where immediate intervention from medical experts is needed in cases of emergency [33].

In conclusion, EUMTS will contribute to providing a safe, seamless environment for the prediction of pre-term delivery so that immediate interventions by medical professionals can be applied. Pre-term babies may receive appropriate care immediately after birth, before being exposed to infection or contamination, thereby preventing the development of disabilities. Future research should include imbedding the solution algorithm inside a practical EMG acquiring device and performing real tests to measure the power consumption and real-time performance. Moreover, a compatible smartphone app that provides support and advice to the pregnant women should be developed.

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