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# Robust and secured telehealth system for COVID-19 patients

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## 1. Introduction

From the beginning, the world has seen pandemics, some notable ones being the Antonine plague, Cyprian plague, Justinian plague, American plagues, Great Plague of London, Great Plague of Marseille, Flu pandemic, American polio, and the Spanish Flu pandemic [1]. The Spanish Flu pandemic had extensive effects worldwide, with an estimated 50 million deaths [2]. Several factors, as well as World War I, added to the spread of the pandemic virus, which frequently triggered high-symptomatic attack rates and severe illness. Main accomplishments over the last 100 years have been made in influenza prevention, diagnosis, and treatment [3] though, the prospective for a severe pandemic to develop remains unaffected. Considerate substantial social disturbance and load of infection from the 1918 pandemic can support us to imagine the potential effects of an extraordinary sternness pandemic [4].

According to statements in the publication by Ref. [5], in December 2019, an unknown pneumonia type came to light in Wuhan city, Hubei Province, China. The International Committee on Taxonomy of Viruses (ICTV) identified the virus causing this as a strain of a coronavirus similar to that causing the severe acute respiratory syndrome (SARS). SARS was a pandemic that had also occurred in China in the year 2003. The ICTV named the new pneumonia type as SARS coronavirus 2. The other names associated with this disease are COVID-19 short for coronavirus disease 2019 and 2019-nCov meaning the 2019 novel coronavirus. According to Ref. [6], patients suffering from the disease will have symptoms of fever, dry cough, and tiredness. In addition to these, some patients may experience headaches, pains, nasal congestion, conjunctivitis, sore throat, diarrhea, loss of taste or smell, or a rash on skin or discoloration of fingers or toes. The Ref. [6] has also provided information as to how the virus spreads. The virus is said to be

spread through droplets coming from the nose and mouth. The virus sticks to surfaces and anyone who comes in contact with such surfaces will get the virus. If the person who has been in contact with the virus touches any of their body openings, they shall be well infected by the virus as it enters the interior of the body. The coronavirus has an incubation period of up to 14 days according to the Ref. [6]. This means infected people may be unaware of it, and can continue to spread the virus until the symptoms show up.

The severe acute respiratory syndrome coronavirus (SARS-CoV), H5N1 influenza A, H1N1 2009, and Middle East respiratory syndrome coronavirus (MERS-CoV) cause acute lung injury and acute respiratory distress syndrome which leads to pulmonary failure and consequence in fatality. It was assumed that these viruses infect only animals up until the world observed a SARS epidemic affected by SARS-CoV, 2002 in Guangdong, China [7]. Only a period later, a new pathogenic coronavirus, identified as MERS-CoV initiated an epidemic in Middle Eastern countries [8,9].

The first case of novel coronavirus pneumonia (COVID-2019) was discovered in December 2019 in Wuhan of Hubei Province in China, Corona 65–125 nm in diameter represents characterizes crown-like spikes on the outer surface of the virus; thus, therefore, it was named as a coronavirus. The COVID-19 epidemic has become a public health incident that desires universal care and cooperation.

People all over the world have been instructed to stay in their homes, escape congregations, regularly wash their hands, continue at least 1–2 m distance (“social distancing”), and bypass touching their faces to escape or deferment transmission of 2019-nCoV. These guidelines would strictly hamper routine actions if applied at a high level of fidelity, so voluntary obedience is possible to be uneven at best [10,11].

## 1.1 Big data and pandemic

Big data refers to large amounts of data that cannot be processed by conventional means [12] but rather need technologically advanced algorithms for analysis and identification of patterns. Big data is based on technology for processing, analyzing, and finding patterns. The characteristics of big data have been listed by Ref. [13] as volume, velocity, variety, value, and veracity. These characteristics were explained by Ref. [14]. Volume refers to the amount of data that is generated and processed, velocity is the rate at which data are transferred between sources and destinations, value is the importance of the data, variety is the data types being handled, while veracity is the accuracy of the data. Authors in Refs. [15,16], have stressed the importance of sharing information during the COVID-19 pandemic. The authors mentioned that information must be shared through all means necessary so that quick actions could be taken against the COVID-19. The authors did highlight that at present there are some practices for information sharing where people are screened at air and seaports, bus terminals, market places, and health centers and scan results shared through smart city networks.

Authors in Ref. [17] suggested that through the use of sensors mounted at different places, data can be distributed well, and in time to keep people updated about the COVID-19 status. They also mentioned that the sensors already in existence for monitoring other

human conditions can be modified to monitor COVID-19. Authors in Ref. [16] further stated that the confidentiality of information should not be left out when sharing through the smart networks. The use of wearables, where a patient would have sensors embedded within them is one approach that is emerging in the area of the Internet of Things (IoT) for real-time remote diagnosis. The sensors pick up physiological parameters such as body temperature, blood pressure, sweat, etc., and through communications device such as a radio frequency identification tag, information is sent to remote medical officers. The remote medical officers may act accordingly, such as by referring the patient to a specialist or recommending treatment for the illness. There are commercial wearable gadgets in place that have been developed for remote patient monitoring [18]. The practice of telemedicine in the outbreak of any virus has a high potential in enlightening epidemiological research, virus control, and clinical case management.

The outbreak of Ebola in 2014 in West Africa alarmed the health professionals concerning the loopholes faced during the epidemics and highlighted the vital role of big data and technology in these situations. Telemedicine has been deemed vital by Ref. [19] because of several reasons. First telemedicine is capable of eliminating situations of overcrowding at medical centers through applications where patients are monitored remotely. It is easier for diseases to be spread in environments where there is overcrowding, therefore telemedicine eliminates such scenarios by remote monitoring. The authors in Ref. [19] also stated that telemedicine can also help in the efficient use of medical resources as it can decide who needs them and who does not. Moreover, patients in areas that have limited medical resources can be helped through telemedicine where the necessary supplies would be delivered to them after remotely learning of the possible infections.

Telemedicine practices started in several countries simultaneously [20]. Telehealth goes back a long way [21]. As far back as 1879, there were needs for using telephones instead of visiting offices personally. A telecardiogram was demonstrated in 1905 by Willem Einthoven when they listened to a baby's cough on the telephone as a diagnosis [22]. In 1910, the transmission of electrocardiograms was demonstrated by two cardiologists based in New York [22]. After the invention of the cardiogram, an idea was put in place for a telecardiogram [21]. In 1948, the first images from radiology were transmitted to other doctors through telephone [23]. In 1924, in a certain magazine, a picture of a doctor diagnosing a patient was seen on the cover [20]. In 1957, experiments were performed by Albert Jutras on teleradiology while the year 1959 saw Cecil Wittsson working on telepsychiatry. In 1961, remote medical diagnosis was performed in space on animals as done by the United States [23]. Around 1990, the Internet became public, and it made telehealth much easier. In the year 2016, telemedicine can be considered to have exploded to widespread use as a consortium named Kaiser Permanente announced that there more consultations being performed remotely than in a physical sense [24]. Kaiser Permanente uses their applications for sending emails, scheduling appointments, online view of tests, and making prescriptions online.

The real-time tools of the IoT not only monitor the spread of disease but also facilitate the emergency response team automatically if these tools and technology are used effectively. When public health workers can effectively couple this world of data to map and track epidemics in real-time, it can show to be life-saving. Employing the tools to detect where the disease might travel next, they can easily forecast the amount and demand of resources and medical workers. Handling health technologies is extremely difficult, and taking all features into account is very challenging. When measuring and applying technologies, we tend to concentration on precise structures, overlooking other and vital features. For instance, when evaluating diagnostic technologies, we incline to emphasize correctness data (such as test sensitivity and specificity) and not on what matters for patients, such as diagnostic effect and following therapeutic results. Telehealth can bond numerous medical organizations into one virtual network, controlled by the principal clinic. This network can comprise different physical locations: central and remote medical facilities such as hospitals, clinics, physicians' offices, and all registered patients within their localities. The following tasks should be the priorities: tele-conferencing, secure messaging, electronic scheduling, analytics, and laboratory reports, billing and e-payment, radiology file uploads, integration with electronic health record systems, and e-prescribing.

### *1.1.1 Artificial intelligence*

In addition to the diagnosis of diseases, artificial intelligence (AI) has also been applied in the treatment as highlighted by Ref. [25] and as such may be used against COVID-19. It has been used before in Japan where a recommendation for the right drug for patients suffering from hematological malignancies was made by AI. In the development of vaccines by Ref. [26], AI was also applied where the process of the discovery of the vaccine was sped up.

The use of AI against COVID-19 as a prediction tool was analyzed by Ref. [27]. The authors did look into two existing commercial AI sites that predicted COVID-19 well in time. These sites are referred to as Bluedot and Metabiota. Bluedot is said to work by scanning over 10,000 sources of information in 60 languages. From the search results, Bluedot looks into areas that could be of high concern through the use of clustering tools. The found news are then sent to customers regarding the most likely regions to be hard-hit by the disease, and any other relevant information like how it spreads, best practices against it, etc. Bluedot is said to have predicted the 2009 pandemic of the H1N1 influenza virus, the 2014 Ebola outbreak, 2016 Zika virus, and the COVID-19 before it was officially declared a world pandemic. In addition to Bluedot, there is another prediction tool known as Metabiota which uses AI, Big Data, Natural Language Processing, and Neuro-Linguistic Programming to collect and process large amounts of data from different sources. The sources may be official or unofficial and they include social media. Metabiota is said to mostly benefit insurance companies, nonprofit organizations, and

governmental agencies so that they can make the right decisions. Metabiota is said to have predicted both the 2014 Ebola outbreak and the current COVID-19 before they were declared emergencies.

## 1.2 Critical data transmission in telehealth

The advantages of using remote patient monitoring were stated by Ref. [28]. first as eliminating the need for medical personnel to physically monitor the patients and secondly eliminating the possibility of infections between the patients and medical personnel as the routine spot checks would be minimal. Sensor data feature and reliability is a worldwide obligation. For diagnostic applications, large regulatory footprints may have to be considered. The real equipment used in the sensor can also have a significant effect on the excellence and correctness of the information. While economical sensors can upsurge affordability and right of entry to information, this could derive at the expense of information feature which is key to elude a gratuitous incorrect apprehension. The placement of thousands of nodes for wireless sensor networks is the biggest issue that has not yet been solved appropriately. The biggest issue of consistent data transmission and reception can be alleviated by a reliable error control coding scheme [28].

### 1.2.1 Error correction mechanisms

There are two types of error correction mechanisms available [29]. The mechanisms of error correction maybe by sending redundant data and the second is by allowing the receiver to detect errors and request for a retransmit. There are different sources of error in communication links such as noise or electrical distortion, burst, random bits, and cross talk and echo. There are different sources of noise such as electrical pulses, radio waves because of inductive devices like motors and transformers. Burst errors are because of large sums of data bits when several interconnected bit errors are occurring at many sites. Random-bit errors occur because of the accidental changes in bit transmission sequences. Cross-talk and echo occur in transmission lines that are close to each other which usually have mutual inductance. There various techniques as well for error detection. These include a simple parity check, two-dimensional (2D) parity check, checksum, and cyclic redundancy check. The simple parity checking works by sending a parity bit along with the code words to be transmitted. If there is an odd number of 1's within the parity bit, the parity bit used is 1 and 0 parity bit is used if the codeword has an even number of 1's. The 2D parity check is said to influence the performance. Here the data bits are organized in the form of a table and parity computed at the receiving end. In the checksum technique, data bits are segmented to a certain number of chunks with each one having a certain number of bits. The segments will then be added using 1's complement.

This paper proposed a secure and robust Telehealth system coupled with a highly robust decoder to process, analyze, and transfer patient data in real-time. Fig. 17.1 shows the proposed Telehealth system.

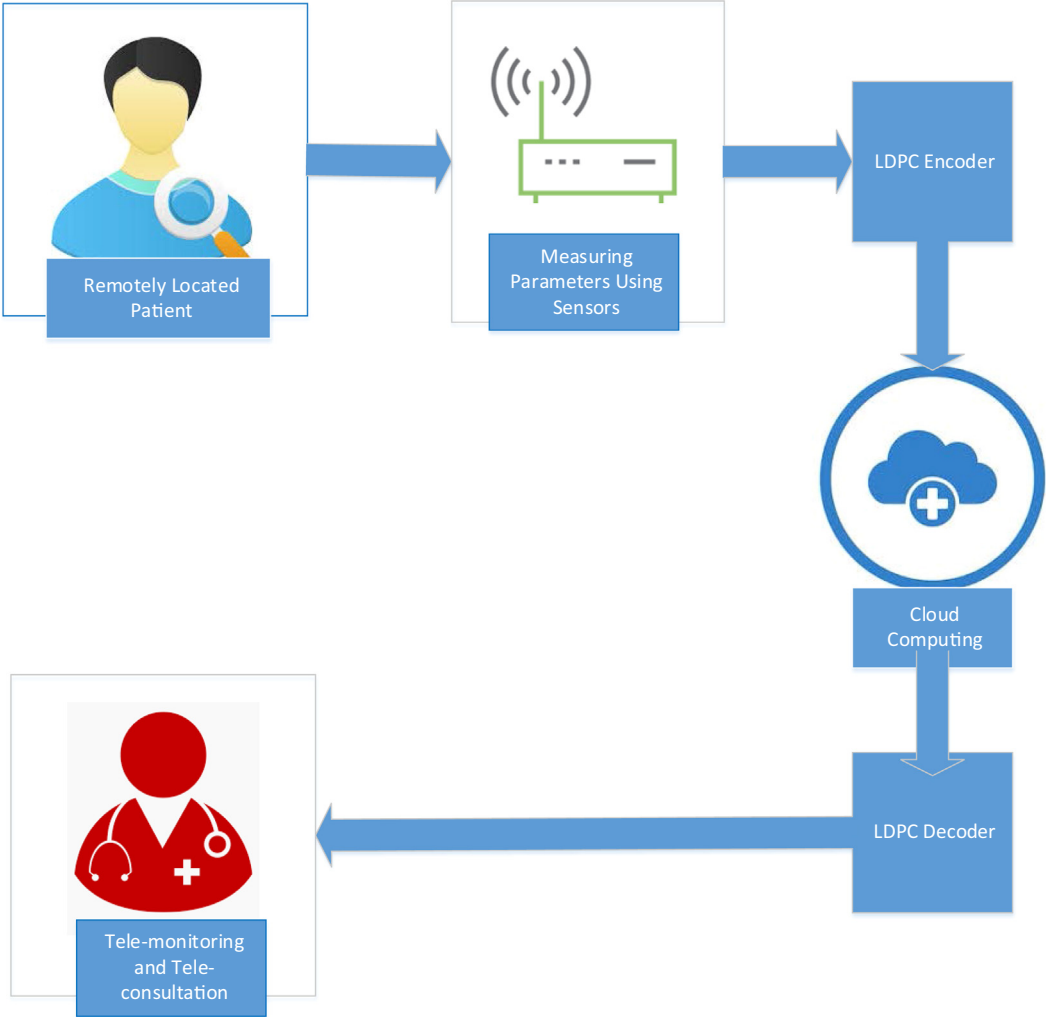


FIGURE 17.1 Proposed telehealth system coupled with low-density parity check encoder-decoder.

## 2. Error mitigation codes for telehealth system

In the current age of technology, significant growth in the use of smart devices in various applications like the IoT [28] has been observed. The important features of the IoT used specifically for crucial applications like eHealth are adaptability, fast flow of information, data reliability, and of course the computational complexity. Reliability is one of the important aspects of the IoT network which ensures the completeness of data [30]. To ensure data reliability and integrity in the presence of Gaussian noise and other types of

attenuation during the wireless transfer of data in IoT-based telehealth system, some additional features are required to include in the system to protect data at risk and this will simply mean that we can estimate the data for getting the right message.

For maintaining data reliability and integrity in the presence of environmental noise, error mitigation codes are the only choice to retrieve the desired information completely. Therefore, the reliability of information is one of the main concerns in application-specific IoT like telehealth. Reliability and completeness of the information are one the major research question. In this proposed method, newly developed methods of constructing regular and semi quasi-cyclic low-density parity check matrix (LDPCM) [31], which are based on the structure of Sarrus and geometric designs. Because of the cyclic structure of these codes, these LDPCMs are fast in computation and also consume less storage memory.

As in the IoT-based telehealth, there might be few bytes to transmit or it can be large data. To achieve this variable data throughput in IoT for biomedical application, low-density parity-check (LDPC) codes can play a key role to achieve the parallelism in encoding and decoding. The quasi-cyclic nature of the LDPC codes [31] naturally keeps parallelism in encoding and decoding, and high-data rate encoder and decoder can be realized by such parallelism. Adaptive rate compatibility to select an arbitrary length of transmitted codeword bits from parental code output and a variable code length are other important functionalities of LDPC coded IoT channel.

To achieve the goal of reliable communication, LDPC-coded message can be transmitted from source node to destination node directly. But in areas where the source node cannot transmit directly to the destination node, the relay channel is required to maintain reliable communication as shown in Fig. 17.2 [32].

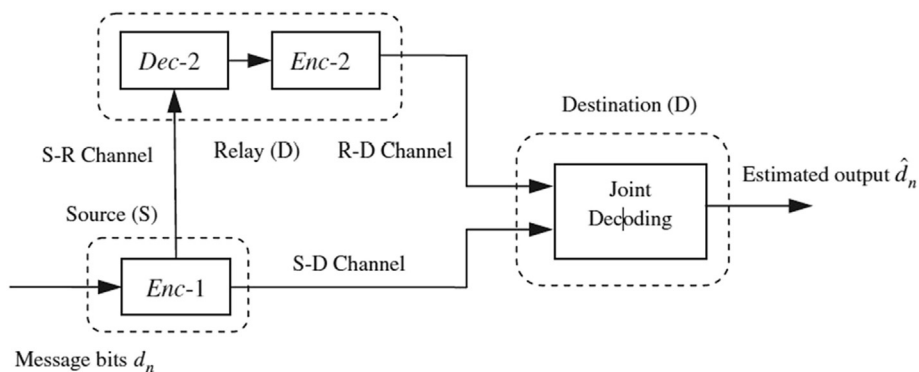


FIGURE 17.2 Low-density parity-check–coded relay cooperation and joint decoding.



## 2.1 New reduced complexity low-density parity-check Min-Sum decoder

For the two consecutive decoding iterations, the LDPC Min-Sum decoding algorithms presented in Refs. [33–35] are stated as follows:

- (a) At variable node processing, if the signs of the current and the previous variable node messages do not change, this means there is not a big change in magnitude.
- (b) Similarly, if the sign of the present message is different than previous messages, this shows that an increase in the magnitude is large.

Different than the two algorithms in Refs. [33,34], we use a normalized factor to slow down the magnitude overestimation at the variable node when there is a sign change. This technique reduces the computational complexity.

During the two consecutive iterations, the overestimation of magnitude during the variable message node processing at the present iteration, the signs of the current and the previous messages are compared. If there is no sign change, the message has remained unchanged, and if there is a sign change, a normalization factor is multiplied to reduce the size of the magnitude.

A hardware implementable factor of 0.25 is used which is simply equivalent to shift by two in a shift register.

In Eq. (17.1), the variable node message is stored after calculated at the  $k$ th iteration before using for updating the posterior information  $\widehat{\gamma}_n$  as  $\alpha_{ji}^{k,tmp}$ .

$$\alpha_{ji}^{k,tmp} = \gamma_i^k - \beta_{ji}^k \quad (17.1)$$

Comparing the signs of the current variable nose message  $V_{ji}^{k,tmp}$  and the previous variable node message  $V_{ji}^{k-1}$ .

$$\text{If } \text{sign}(\alpha_{ji}^{k,tmp}) \neq \text{sign}(\alpha_{ji}^{k-1})$$

Then update the message as:

$$\alpha_{ji}^k = sf(\alpha_{ji}^{k,tmp}) \quad (17.2)$$

$$\text{else if } \text{sign}(\alpha_{ji}^{k,tmp}) == \text{sign}(\alpha_{ji}^{k-1})$$

Then update the message as:

$$\alpha_{ji}^k = \alpha_{ji}^{k,tmp} \quad (17.3)$$

Different from both the LDPC decoding algorithms [33,34], the currently stored message and the previous message are not summed up. Also, a single scaling factor is used only when there is a sign change which greatly reduces complexity and shows a good effect on the overestimation in magnitude. This process is shown in Fig. 17.3.

The scaling factors  $sf$  such as it can be easily implemented in hardware and also gives a good approximation to the variable node message which results in error reduction. On

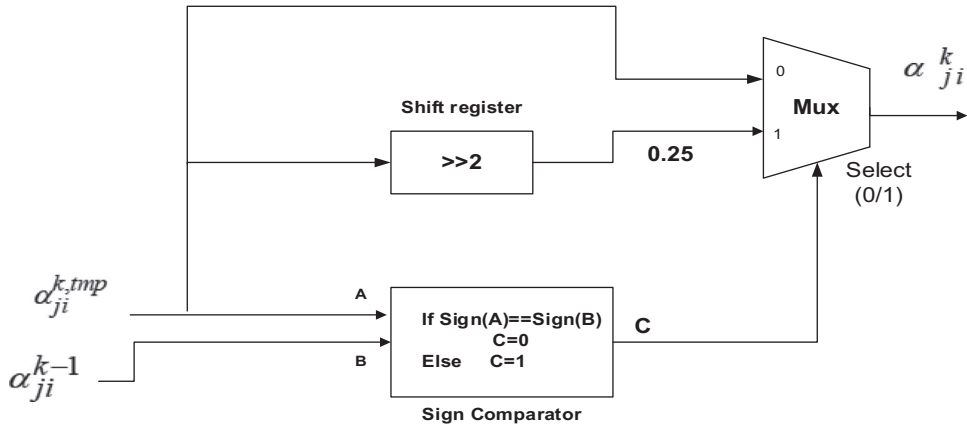


FIGURE 17.3 Message correction at variable node processing.

the other hand, if the signs are not the same, then the change in magnitude is considered to be large and needs to be modified with a factor to avoid magnitude overestimation.

Eqs. (17.2) and (17.3) give good bit error rate performance achievement while at the same time, the cost for hardware is also reduced as we do not need any additional multiplier and adder.

In this proposed algorithm, the previous message is not required to add which simplifies the hardware.

### 2.1.1 Simulation results

Let  $c = \{c_1, c_2, \dots, c_j, \dots, c_n\}$  be a codeword in  $\epsilon$ , then this binary sequence is modulated with binary phase-shift keying (BPSK) where 1 is modulated as  $-1$  and 0 as  $+1$  i.e.,  $x = 1 - 2c$ . These BPSK-modulated binary sequences are transmitted over the additive white Gaussian noisy channel and the following sequence shown in Eq. (17.4) is obtained at the receiver.

$$y = x + n \quad (17.4)$$

Here  $n$  shows the additive white Gaussian noise  $n \rightarrow N(0, \sigma^2)$  with zero mean and two-sided power spectral density  $\frac{N_0}{2}$ . For the received bit  $y_j$ , the hard decision bit  $z_j$  at the receiver is given by:

$$z_j = \begin{cases} 1 & \text{if } y_j < 0 \\ 0 & \text{else} \end{cases} \quad (17.5)$$

The received sequence is considered correct if the  $i^{\text{th}}$  syndrome  $s_i = 0$  of the  $j^{\text{th}}$  received bit defined over  $h_{ij} \neq 0$ , given as follows:

$$s_i = \sum_{j \in N(i)} h_{ij} z_j \quad (17.6)$$

**Table 17.1** Typical health parameters.

Parameters	Respiratory Rate/minute	Oxygen saturation	Temperature	Heart rate	BP
Normal range	12–16	69–90.5	37°C	60–99	80–120
Abnormalities	10	97	38	50	140

If  $s_i \neq 0$ , then the received bit is in error and needs to be corrected by using the LDPC decoder. The proposed LDPC decoder run for a predefined number of iteration to correct the received bit.

The initial a priori information is defined for the decoder as follows:

$$\gamma_n = \log \frac{P(x_n = 0|y_n)}{P(x_n = 1|y_n)} \quad (17.7)$$

The parameters as shown in [Table 17.1](#) are selected and encoded before transmission for the Telehealth application. The encoded message is transmitted over the noisy and congested channel and decoded at the destination as shown in [Fig. 17.3](#).

[Table 17.2](#) shows values that are continuously monitored remotely. Reliable transmission of these parameters via a communication channel is very important. The following frame is encoded and transmitted wirelessly to the end-user.

Data Frame “Resp R=10,Oxy S=97,Temp T=38,Heart R=50,BP=140.”

This frame is encoded by the newly developed matrices for high performance as in Ref. [\[31\]](#).

It is observed that if the message is sent without error mitigation code, then it is not understandable for the team working at remote positions.

The other two scenarios just show how the message is recovered completely by iterative LDPC decoder at node B. The message is first encoded at node A before transmission by using a structured LDPC parity check matrix of size (984, 492) specially designed for this transmission with rate compatibility of message length up-to 492 bits. The patient data from the sensors are encoded and transmitted to care providers in real-time using the newly designed secured decoder.

**Table 17.2** Transmission and reception of abnormal values only.

<b>1.</b> Uncoded transmission and reception	
Parameters received	"Resp R<10oly [=97-Very" T=s0\$HearT R=50,BP=142'
<b>2.</b> LDPC coded transmission and reception (3 iterations)	
Parameters received	'dResp R=10,Oxy S=97 Temp T=38,Heart" R=50,BP}142'
<b>3.</b> LDPC coded transmission and reception (5 iterations)	
Parameters received	Resp R=10,Oxy S=97,Temp T=38,Heart R=50,BP=140'

### 3. Conclusion

With the advent of the IoT, Telehealth is now a module of great importance in dealing with pandemics. It is a convenient way of taking care of patients. Patients may be in different distress conditions such as being unable to move or in quarantine. As such Telehealth has made health care easier by remote diagnosis, tests, and prescriptions. Medical resources can be shared quite efficiently as telehealth makes it easier by deciding who needs them. With overcrowded medical centers, Telehealth allows for consultation continuity and allows for the minimal transmission of pathogens among people.

The privacy of the patient data shared through the networks should be maintained. Different ways of protecting patient data must be employed, such as cryptography. Errors in patient data transmission should be mitigated to avoid wrong decoding of the patient data which may lead to doctors making the wrong prescriptions. Medical technology has extensively been considered as a coherent technology-based system to attain detailed people objectives to overcome distress and improve health. A big number of individuals, equipment, and sensors are linked digitally and produce a huge capacity of data.

However, the frequent usage of the Telehealth system also upsurges to severe apprehensions about the recovery, storing, investigation, and safety of patent data and healthcare experts. This paper proposed a real-time Telehealth system for an outbreak like COVID-19. The proposed system developed error mitigation codes for the COVID-19 epidemic to retrieve the desired information securely and efficiently in realtime. With more telehealth systems coming up, more health is expected to be generated and as such, there is a need to handling large volumes of the health data without compromising its accuracy, accessibility, and confidentiality. The scope of this work shall in the future extend to ways of compressing large amounts of data to deal with congestion, as more telehealth devices are coming up and will implement machine learning techniques for diagnosis.

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