An innovative approach to integrate unequal protection-based steganography and progressive transmission of physiological data

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Abstract

Evolving digital technologies in remote health monitoring require an energy-efficient method for secure and reliable transmission of patient's/user's confidential information from the sensor nodes to the cloud/medical server. Thus, a united scheme of the physiological signal steganography and its communication by benefitting from the unequal significance between different parts of the physiological data are emphasized. We believe higher steganography coding strength and more robust source-channel coding would protect extremely vital parts of the physiological data. Therefore, data integrity and transmission efficiency of packet information achieved in a resilient way. We formulate our idea of joint steganography-source-channel coding (JS^2C^2) as an optimization problem to simultaneously securing and minimizing the transmission energy consumption. A low-complexity deep learning-based ECG classification algorithm along with its secure and energy-efficient neural JS^2C^2 transmission for real-time monitoring has been realized. The optimal parameters for our united framework have been calculated by JS^2C^2 optimization method. Our steganography algorithm unequal steganography embedding (USE) achieves very low wavelet-based weighted percent root-mean-squared difference lower than 0.5%. Furthermore, the high correlation between cover and stego and low end-to-end mean-square error (MSE) indicates resilient imperceptibility and maintains the diagnosability of the physiological signal. Moreover, low MSE between embedded and extracted data validates that embedded confidential data has been extracted with negligible distortion. In addition, for the given distortion, the USE-based framework's energy consumption is much smaller (by 55% in typical application scenario) as compared with the equal steganography embedding-based approach's energy consumption.

Keywords Electrocardiography (ECG) · Unequal error protection (UEP) · Unequal steganography embedding (USE) · Joint steganography source coding (JS^2) · Joint source-channel coding (JSC^2) · Joint steganography-source-channel coding (JS^2C^2) · Deep learning (DL) · Security · Correlation · End-to-end distortion · Energy efficiency

1 Introduction

In the history of error-resilient approaches for increasing the robustness of wireless transmission of data, security is always paid less attention, whereas in telemedicine, healthcare data security is vital, e.g., to remain health insurance portability and accountability act (HIPAA)-compliant, healthcare providers need to ensure that their user's/patient's confidential information is secure and

encrypted to prevent a data breach or cyber-attack. Since the demand for secure and energy-efficient techniques for wireless transmission of healthcare data is growing, it requires a framework for it and is the focus of this paper.

Figure 1a illustrates the conventional approach of the transmission scheme where all the encoders are separate and try to achieve security, efficiency, and reliability. The secure communication system employs a three-step encoding process for the transmission of physiological

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Fig. 1 Secure and energy-efficient transmission scheme: **a** conventional approach and **b** proposed JS^2C^2 approach

data: (1) the security encoder, e.g., encryption; (2) the physiological data are compressed with a source coding algorithm to remove the inherent redundancy, and to lower the amount of transferred information; and (3) the compressed bit-stream is encoded with an error-correcting code, which enables resilient transmission against channel errors, and then modulated. In the past, communication efficiency and reliability are discussed by various researchers. For example, Shannon's separation theorem proves that the two-step source and channel coding approach is optimal theoretically in the asymptotic limit of infinitely long source and channel blocks [1]. However, to avoid extreme latency, bandwidth, and/or energy constraints, computationally demanding long-block length source and channel coding techniques are infeasible and replaced by *joint source-channel coding* (JSC^2) [2] in order to meet the requirement of emerging applications from the Internet-of-Things (IoTs), but security encoding is never integrated with JSC^2 . To the best of our knowledge, there is no study/research, which unites all three: security, efficiency, and reliability for wireless transmission.

In Fig. 1b, our proposed *joint steganography-source-channel coding* (JS^2C^2) approach where wireless physiological signal transmission that does not rely on explicit codes for either steganography, compression, or error correction; instead, it directly maps the raw physiological signal values to the complex-valued channel input symbols. The basis of our idea to join all three steganography, compression, error correction together is: Feature distribution analysis of physiological signal e.g., *Electrocardiogram* (ECG) in the wavelet-domain uncovers the fact that lower spatial frequencies are perceptually more crucial than higher spatial frequencies. Thus, the idea of *Unequal Error Protection* (UEP) is not only applicable to JSC^2 can also be applied to steganography; steganography is an assuring technology to maintain the security of confidential information, consequently, the *unequal embedding strength* (UES)-based steganography called *unequal steganography embedding* (USE) is implemented [3, 4]. Furthermore, the unequal importance of wavelet-based source-coded bits is inspected. Inherent similarities within the sub-bands infer that different wavelet-based source coding can be joined with UES-based steganography. Additionally, the uneven significance of source-coded physiological signals is studied. Any rate-compatible channel code will enhance the performance of the communication over erratic channels even more. UES-based USE joined with JSC^2 's UEP achieves high confidentiality and reliability because both crucial stego data and physiologically significant elements of the signal are protected by extra strength. As a result, crucial information is greatly protected by JS^2C^2 .

Our JS^2C^2 has been employed in real-time health monitoring where emergent *wearable healthcare systems* (WHS) are transforming the way of providing healthcare as both patients and healthcare providers want health to be monitored outside of the clinical settings. Figure 2a illustrates the architecture of a general WHS environment. It consists of wireless sensing devices that form a distributed wireless network around the body of the person who wears them. There are a variety of popular wearable sensing devices but are not capable of measuring the reliable health status of the user. Contrariwise, an abundant of sensors that measure physiological parameters but are not in a wearable form. Wearable biomedical sensing devices are therefore the subgroup of devices able both to quantify physiological parameters and worn. These sensing devices continually monitor numerous types of health information from the user and wirelessly communicate this to a base station (BS), for example, smartphone, smartwatch, or laptop. The tiny ECG-sensing device on the user's chest and communicates wirelessly with smart devices. The computationally intensive *deep learning* (DL) model component has been implemented in smart devices. Moreover, the DL algorithms in device process the measured health

Fig. 2 **a** An architecture of a general wearable healthcare systems (WHS) and **b** the Neural JS^2C^2 : secure and energy-efficient real-time monitoring framework

information, displays them to the user and may relay them to a medical cloud for long-term storage and for access by caregivers and/or any medical decision support artificial intelligence, complex *deep neural networks* (DNNs) models for further diagnosis. Hence, wireless communication of physiological signal plays a significant role in remote health monitoring and has the potential to significantly improve the quality of life for patient's/user's.

DL models employed in modern computational-efficient mobile/smart devices for further predictions of health complications from the collected data from wearable sensing devices. DNNs are usually optimized using gradient-based approaches such as back-propagation. However, it is possible to optimize DNNs using a simple

genetic algorithm (GA) and that GAs are a competitive substitute to gradient-based approaches when applied to reinforcement learning (RL) tasks. The key benefit of employing WHS for healthcare is that it eliminates all spatiotemporal limitations of conventional healthcare. An individual's health now observed all times thus offering them better-quality care. Patient's/user's confidential information security, communication energy consumption reduction, and minimizing the end-to-end physiological signal distortion are key to the success of the implementation of any WHS and remote monitoring application in health care. Figure 2b demonstrates our JS^2C^2 approach for WHS where pre-trained DNN-based *Neural JS²C²* is used which is further trained by user-specific physiological data by transfer learning concept [5] for optimal parameters calculation then uploaded for real-time monitoring. The beat detection process is beyond the scope of this paper, as many highly accurate (> 99%) beat detection algorithms have been reported in the literature [6, 7].

This paper comprises our preliminary work in [3, 4], wherein an innovative idea proposed to make wireless scalable physiological signal transmission secure and energy efficient called *joint steganography-source-channel coding* (JS^2C^2) [3]. In [4], we motivated by UEP-concept and applied it to steganography called *Unequal Steganography Embedding* (USE). However, the work in [3, 4] did not address that the JS^2C^2 as an optimization problem e.g., DNNs and how to approach to solve the optimum rate allocation problem associated with it. Furthermore, paper [3, 4] are only small case studies where we studied the inherent similarity of 'UEP-based USE' and 'UEP-based joint source-channel coding (JSC^2)' which leads them united. In this journal version paper, we propose a systematic and holistic framework, which will lay the generic foundation for security, energy efficiency, and reliability of wireless data transmission which did not exist before, with regard to how to integrate steganography, source coding, and channel coding in a unified platform. Moreover, how to solve the rate allocation problem for the joint design of steganography embedding, source coding, and channel coding and theoretical framework to this optimization problem considered.

In this paper

- A complete analytical study presented for progressive transmission of source-coded steganographed data i.e., *joint steganography-source-coded* (JS^2) data along with UEP-based rate-compatible channel coding. Furthermore, the role of UEP in making the transmission secure, energy efficient, and reliable are discussed in detail. In addition, we set the mathematical formulation of distortion for steganography, JS^2 , JSC^2 , and JS^2C^2 .

- Moreover, we formulated the idea of JS^2C^2 as an optimization problem to simultaneously securing and minimizing the transmission energy consumption. DL-based *Neural JS²C²* has been employed for the optimal parameters, any simple or complex optimization technique can be applied. The JS^2C^2 -optimization pseudo-code is proposed to solve the rate allocation problem.
- In addition, the local pre-diagnosis, i.e., the insertion of local embedded computing platform for important data analysis in real-time, makes WHS more energy efficient and avoids any potential latencies as the conventional assumption that everything will be in the cloud/data centers and medical data transmission is always on—that's just not realistic. Furthermore, by leveraging artificial intelligence (AI)/machine learning (ML) and DL algorithms on a smart device that is physically near to critical IoT sensors, healthcare providers lookout for potential warning signs and do scheduled protection to avoid unexpected, and costly surprises. This saves time, improves privacy, and reduces network traffic. A low-complexity *convolutional neural network* (CNN)-based ECG classification algorithm along with its secure and energy efficient *Neural JS²C²* transmission for real-time monitoring has been realized. As many good accuracy pre-trained image recognition DL models [8] such as GoLeNet [9], AlexNet [10], SqueezeNet [11] can be trained by ECG data by using the transfer learning concept, GoLeNet is trained using the continuous wavelet transform (CWT) of normal, arrhythmia, and congestive heart failure category ECGs.
- Additionally, for the given distortion, a comparison presented for the USE-based framework's energy consumption with conventional *Equal Steganography Embedding* (ESE)-based approach's energy consumption.

The major focus of our work is to integrate JS^2C^2 with security and efficiency. The choice of JS^2C^2 parameters are limited and exhaustively listed for the DNN model. Hence, they can be calculated with either the simple or any other complex optimization method, but they would not affect the performance of real-time JS^2C^2 transmission schemes, which is the novelty of this paper because we proposed this innovative method to coherently secure ECG data with steganography in our created JS^2C^2 framework.

The rest of the paper is organized as follows: The overview of relevant research is discussed in Sect. 2. Section 3 demonstrates the conceptual framework and problem formation and Sect. 4 exhibits distortion analysis and

optimization of the scheme. The JS^2C^2 -optimization is proposed to solve the JS^2C^2 's rate allocation problem. Experimental results are demonstrated in Sect. 5. Finally, concluding remarks are given in Sect. 6.

2 Overview of relevant work

Many researchers have successfully designed data-hiding methods for digital media such as images, audios, and videos. However, only a few authors have focused on embedding secret messages in ECG signals or healthcare systems [12–14]. Data-hiding methods, i.e., ECG steganography approaches, have been applied to ECG signals for securing patient information [15–27]. To protect against manipulations, researchers have presented schemes for digital watermarking of ECG signals [28–31]. To preserve the originality of the host ECG signal, the use of reversible ECG steganography based on wavelet transform has been suggested [32, 33]. Liu et al. [14] propose a steganographic method that can provide private data in the medical system with very secure protection. They used the adaptive pixel pair match (APPM) method to embed digits in the pixel value differences (PVD) of the three pixels and the base of embedded digits is dependent on the differences among the three pixels. The minimal distortion of the pixel ternaries caused by data embedding has been obtained by solving an optimization problem. In [15–18] several ECG embedding methods are proposed. In [15], the patient's private data is embedded into a position called Special Range Numbers (SRN) of the cover ECG signal, causing minimum distortion to ECG. In [16], the authors proposed a low-complexity embedding technique by merging the quantization index modulation (QIM) and least significant bit (LSB) substitution method. However, LSB steganography provides poor robustness to malicious alterations. Wavelet-based steganography which combines encryption and scrambling methods to protect confidential data [17]. Pham et al. use a discrete wavelet transform (DWT) to decompose electroencephalogram (EEG) signals and singular value decomposition (SVD) to embed the watermark into the decomposed EEG signal [19]. Jero et al. [20, 21] presented robust steganography techniques for ECG. Their observations validate that the high-frequency (HH) band is the ideal sub-band to hide data. In [21], steganography in arrhythmic ECG signal is discussed, wherein DWT-SVD is employed to hide patient's confidential data into an abnormal ECG signal's two-dimensional matrix. In [22], P. Ramu et al. proposed the imperceptibility–robustness trade-off studies for ECG steganography using continuous ant colony optimization. Jero et al. [23] also proposed an approach to perform ECG steganography using curvelet

transform. Quantization-based digital watermark encryption technology on the ECG to protect patient rights and information is proposed in [24]. Transform domains, DWT, DCT, and DFT are adopted to implement the quantization-based watermarking technique. Wang et al. [25] proposed two methods to perform ECG reversible data hiding. Based on coefficient alignment [26], two kinds of ECG steganographic methods were proposed. Regardless of the aforementioned steganography techniques, the main goal that each method must achieve high embedding capacity given a fixed distortion constraint between the cover and stego signal while allowing reliable retrieval of steganographed data subject to a fixed distortion between embedded and extracted data.

The JSC^2 methodology is widely considered for the progressive communication of source-coded data [34]. Said and Pearlman [35] designed set partitioning in hierarchical trees (SPIHT) for source coding, rate-compatible punctured convolutional (RCPC) coding for scalable multimedia bit error correction. In addition, to limit the error propagation and error detection cyclic redundancy check (CRC) is used. The rate-congruent codes such as turbo codes [36], low-density parity check (LDPC) codes [37] and RCPC codes [38], offer UEP-based channel error protection for progressive transmission. UEP in the case of unequal source block size was addressed in [39], in which the SPIHT bit-stream was divided into three classes according to different error immunities. RCPC channel codes are applied to source packets to obtain improved performance for memoryless channels. In addition, the problem of finding the optimal rate allocation was discussed in [40]. Chande et al. [41] solved the problem by using dynamic programming. Their research also examines UEP and unequal erasure protection in the context of progressive image transmission. In [42] by applying different channel code rates for different kinds of bits (e.g., sign bits, significance bits, etc.) of SPIHT encoded data. Compressed bit-streams are separated into different layers. Each layer effect in received quality due to channel constraint decides the priority of the layer and the required level of UEP. In brief, in UEP schemes [34, 43–46], individual packets of fixed source bits are secured by various rates channel code by variable parity bits. Consequently, the packets might have different total lengths with a fixed number of source bits. In [46], the packetization scheme and the rate optimization for progressive transmission are discussed. Instead, other schemes [39, 47–53] employ fixed-length channel packets, i.e., all packets have a fixed length after channel coding. As far as we know, there is no integration of data embedding and JSC^2 .

In the past, the efficiency and reliability of communication are discussed by various researchers. However, security is paid less attention and steganography is never

joined with source-channel coding. By integrating steganography with JSC^2 , we introduced security to efficient and reliable communication of user's/patient's confidential data in telemedicine. Security is very important because to remain HIPPA-compliant, healthcare sectors need to guarantee that their user's confidential information is secure and encrypted to avert a data breach or cyber-attack. Our work combines steganographed medical signal to JSC^2 transmission. The uniqueness and significance of UEP-based JSC^2 methodology is that the significance diversity of the medical signal is used for both steganography and source-channel coding simultaneously. Such joint exploitation has a significant benefit with the biomedical signals having unequally important components. USE method employs the benefits of the fact that diverse segments of the medical signal, e.g., an ECG signal, have an intrinsically uneven effect on both the medical attributes of the steganographed signal and transmission qualities of the biomedical signals in wireless channels. This disparity of biosignal is used in our proposed JSC^2 approach and significance-diverse medicinal information are steganographed with uneven embedding strengths in a joint design with source-channel coding. Our group has done numerous research associated with energy-efficient transmission [54–60]. Papers [59, 60] have extensively investigated these unequal importance properties of the compressed signals. Wavelet-based compression algorithm, e.g., SPIHT, exploits the inherent similarities within the subbands in a wavelet decomposition of a steganographed ECG and codes the most important wavelet transforms coefficients first and transmits the bits. In short, a wavelet-based source coder creates a layered bit-stream according to their relative importance. Moreover, the scalability stimulates sequential dependency among the compressed bit-streams that call UEP. UEP in the form of extra protection for the beginning part of the source coder bit-stream, fewer for the central part, and slight or even no protection at all for the last part by the channel coder makes the transmission even more efficient and reliable. In short, optimal JSC^2 for USE has been realized in the form of UEP in which different channel coding is applied according to the significance of the steganographed source-coded block and improves the overall performance of JSC^2 against channel errors. In this paper, we present a complete analytical study and propose a theoretical framework for this optimization problem for the joint design of steganography, source coding, and channel coding.

In recent years, DL [5, 8–11, 61–92] has shown its overwhelming benefit in many areas, such as computer vision, robotics, natural language processing, and physiological signal pattern recognition/classification due to its advanced algorithms and tools in learning complicated models. A series of successes have also been reported by

DL with the approaches based on CNN for visual tasks such as image classification and recognition [8], object detection [92], and so on. Moreover, DL has also shown great potential to revolutionize communication systems. DL adopts a DNN to find data representation at each layer, which could be built by using a variety of ML techniques, including supervised ML, unsupervised ML, and Reinforcement Learning (RL). Faust et al. [61] reviewed 53 papers on DL methods applied to healthcare applications based on physiological signals such as electromyogram (EMG), electroencephalogram (EEG), ECG, and electrooculogram (EOG). In the content review, they understood that DL performs better for considerable big and varied datasets than classic analysis and machine classification methods. Their review paper depicts the application of various DL algorithms used, but in the future, it would use for more healthcare areas to improve the quality of diagnosis and there may be more advanced DL algorithms focused on the early detection of diseases using physiological signals. In [62, 62–71], the various researcher proposed DNN models for ECG healthcare confirming that a DNN model is a powerful tool for heartbeat pattern recognition and classification. Furthermore, neural networks (NN) are also used for steganography and watermarking [72–79]. Mun et al. [76] use gradient descent to do the encoding. An end-to-end approach to steganography using adversarial networks are proposed [77, 78]. Uchida et al. [79] embed watermarks into the weights of trained neural networks. Since state-of-the-art recognition achieved by applying DNNs and it has recently shown that channel codes and *joint source-channel coding* [80–83] can also realize by DNNs. For example, E. Bourtsoulatz et al. proposes a *deep joint source-channel coding* technique [80] for an end-to-end communication system for wireless image transmission that directly maps the image pixel values to the complex-valued channel input symbols. Their approach is based on unsupervised DL methods, in particular, the autoencoder architectures [90, 91], where the encoding and decoding functions are parameterized by two CNNs and the communication channel is incorporated in the NN architecture as a non-trainable layer. Additionally, DL has recently applied to IoT systems [84–89], but none of them applies DL for solving the joint security-transmission problem.

Our main focus is to achieve a secure and energy-efficient transmission framework for the ECG data. In this paper, an innovative way is proposed to coherently secure ECG data with steganography and JS^2C^2 for transmission in our united JS^2C^2 framework. To the best of our knowledge, there is no joint security-transmission framework based on DNN. Here, we employed DNN for our JS^2C^2 framework. A simple optimization method is proposed for its optimum parameters calculation; however, any complex

optimization technique can be employed without affecting the performance of real-time JS^2C^2 transmission schemes.

3 Conceptual framework and problem formation

3.1 The steganography, source, and channel coding algorithms

Due to the constrained-bandwidth of the wireless channels, UES-based steganographed signals must be compressed by efficient source coding algorithms. On the other hand, under the noisy wireless environments, compressed data becomes immensely susceptible. Therefore, it is obligatory for the physiological signal encoder to provide appropriate error resilience qualities to defend the data from the channel errors. Furthermore, it is not only the JS^2C^2 end-to-end performance that is important, but the intermediate performance as well. For example, if a satisfactory reconstruction fidelity is already reached at a low intermediate rate, the receiver saves energy by stopping the decoding. Thus, it is essential to study JS^2C^2 's all individual stages along with their mutual correlation for the performance analysis of the system.

3.1.1 Embedding mechanism: unequal steganography embedding (USE)

Embedding capacity and the extent to which it is secure are the challenges encountered by steganography methods. Since the embedded data amount and distortion of cover signal caused by embedding are reciprocally related. Moreover, the level of substantial alteration in the physiological feature of the cover signal needs to be judiciously put in control. Therefore, it is essential to investigate how steganography has been used efficiently to attain a great level of security in hiding the patient's confidential information. The distortion should be negligible in the physical features of the host signal in order to ensure the success of the diagnosis of the physiological signal after the extraction of confidential data. We believe that this is the first work on UES-based steganography. We prudently use the medical signal's significance diversity for embedding and attained relatively low distortion in comparison to *Equal Embedding Strength* (EES)-based methods. Generally, approximation coefficients are not suitable to be used for embedding stego data because these coefficients carry the maximum information content of the cover and are less tolerant against any numerical changes [4]. Hence, the

most appropriate zone for hiding confidential data is the detail coefficients. In our USE method, embedded coefficients are selected from detail coefficients.

Extraction is the reverse method of embedding. Secret key $\mathbb{K}$ is used to generate a unique sequence $\mathbb{S}_{\mathbb{K}}, \mathbb{I}_i$ for embedding, as well as for the extraction of embedded confidential data. Embedded confidential information has been extracted from the received steganographed signal $\hat{\mathbb{P}}(t)$ by the following steps:

The uniqueness of the USE technique is that it uses the benefits of the fact that various parts of the medical signal $\mathbb{P}(t)$, e.g., different wavelet coefficients within ECG, have an intrinsically uneven influence on the attribute of the steganographed signals. Medical data of distinct significance levels are steganographed with various embedding strengths so that the restored signal quality is well-preserved. This idea of unequal embedding not only achieves high confidentiality but also provides reliability because of distortion $\mathbb{D}_{\text{Steg}}$ in physiological signal $\mathbb{P}(t)$ due to USE is negligible.

$$\min \mathbb{D}_{\text{Steg}}(R_{\text{Steg}}) \text{ subject to } R_{\text{Steg}} \leq C_{\text{Steg}} \quad (1)$$

where $\mathbb{D}_{\text{Steg}}$ is distortion due to USE and R_{Steg} is the embedding rate. The embedding rate must be chosen $R_{\text{Steg}} \in (0, C_{\text{Steg}})$ such that $\mathbb{D}_{\text{Steg}}$ is negligible. Here C_{Steg} is embedding capacity. This is substantiated with our simulation results showing a very low WWPRD and the high correlation between the cover $\mathbb{P}(t)$ signal and the stego signal $\hat{\mathbb{P}}(t)$ embedded with secret data as compared to conventional steganography methods. Hence, $\mathbb{P}(t)$ remains diagnosable after USE, and embedded data has been reliably extracted from the steganographed signal $\hat{\mathbb{P}}(t)$.

Algorithm 1 USE Embedding Algorithm

Embedding Algorithm: $\text{Em} \rightarrow \hat{\mathbb{P}}(t) = \mathcal{USE}_{\mathcal{M}}(\mathbb{P}(t), \mathbb{I}, \mathbb{K})$

Input: Cover Signal $\mathbb{P}(t)$, Confidential Information $\mathbb{I}$, Shared Secret Key $\mathbb{K}$

Output: Stego Signal $\hat{\mathbb{P}}(t)$

Step 1. Information bits set $\mathbb{I} = [\mathbb{I}_1, \mathbb{I}_2, \mathbb{I}_3, \dots, \mathbb{I}_n]$

Step 2. DWT of the Cover Signal

$$\mathbb{P}(t) = \sum_k c_{a,k}^m \varphi(t - k) + \sum_{j=1}^m \sum_k 2^{\frac{j}{2}} c_{d,k}^j \psi(2^j t - k)$$

Step 3. Embedding Strength Vector $\mathbb{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n]$

Step 4. Unique Sequences $\mathbb{S}_{\mathbb{K}, \mathbb{I}_i}$ generated by Key $\mathbb{K}$ and Information bits subset $\mathbb{I}_i$ for $i = 1, \dots, n$

Step 5. information embedded in level- m detail coefficients

$$c_d^m = \{c_{d,1}^m, c_{d,2}^m, \dots, c_{d,n}^m\}$$

$$\begin{cases} c_{d,1}^{m_{\text{Steg}}} = c_{d,1}^{m_{\text{Orig}}} + e_1 * \text{abs}(c_{d,1}^{m_{\text{Orig}}}) * \mathbb{S}_{\mathbb{K}, \mathbb{I}_1} \\ \dots \\ c_{d,n}^{m_{\text{Steg}}} = c_{d,n}^{m_{\text{Orig}}} + e_n * \text{abs}(c_{d,n}^{m_{\text{Orig}}}) * \mathbb{S}_{\mathbb{K}, \mathbb{I}_n} \end{cases}$$

Step 6. steganographed bio-signal $\hat{\mathbb{P}}(t)$ is IDWT

$$\begin{aligned} \hat{\mathbb{P}}(t) = & \sum_k c_{a,k}^m \varphi(t - k) + \sum_k \sum_{j=1}^{m-1} 2^{\frac{j}{2}} c_{d,k}^j \psi(2^j t - k) \\ & + \sum_k 2^{\frac{m}{2}} c_{d,\text{Steg},k}^m \psi(2^m t - k) \end{aligned}$$

Algorithm 2 USE Extraction Algorithm**Extraction Algorithm:** $\text{Ex} \rightarrow \mathcal{USE}_{\mathcal{X}}(\hat{\mathbb{P}}(t), \mathbb{K}, \mathbb{M}) \rightarrow \tilde{\mathbb{P}}(t), \tilde{\mathbb{I}}$ **Input:** Stego Signal $\hat{\mathbb{P}}(t)$, Shared Secret Key $\mathbb{K}$, Size of shared key $\mathbb{M}$ **Output:** Cover Signal $\mathbb{P}(t)$, Confidential Information $\mathbb{I}$ **Step 1.** DWT level- m detail coefficients of Stego Signal $\hat{\mathbb{P}}(t)$
 $\hat{c}_d^m = \{\hat{c}_{d,1}^m, \hat{c}_{d,2}^m, \dots, \hat{c}_{d,n}^m\}$ **Step 2.** Split in n Subbands, find the position $\mathcal{P}$ of steganography and repeat step 3 for n subbands.**Step 3.** set $s = 0$.
$$\begin{cases} \text{For } i = 1 \text{ to } \mathbb{M} \\ s = s + 1/\mathbb{M} * \sum_i \hat{c}_d^m(1, \mathcal{P} + i) * \mathbb{K}(i) \end{cases}$$
Step 4.

$$\begin{cases} \text{If } s > 0 \\ \text{Steganographed Information Bit } \tilde{\mathbb{I}} = +1 \\ \text{Else Steganographed Information Bit } \tilde{\mathbb{I}} = -1 \end{cases}$$
Step 5. Extracted information bits set is $\tilde{\mathbb{I}}$ and reconstructed cover signal $\tilde{\mathbb{P}}(t)$.**3.1.2 Joint steganography-source coding (JS^2)**

Although any compression algorithm among the range of approaches can be applied for source coding, wavelet-based SPIHT is not only simple and provide good results, it can also be truncated at any point with progressive lossy to lossless quality. However, SPIHT bit-stream are sensitive to channel noise. One bit of error might lead to a complete failure of signal recovery at the decoder. The different error immunities bit-stream from source coder are separated in diverse sub-streams classes with distinct protection properties. The studies show that as the bit-plane count increases, the distortion reduction increase nonlinearly. These findings imply that by using an appropriate UEP-based communication approach, potential performance improvement has been attained. Therefore, a more important bit-stream, i.e., higher embedding strength, part of steganographed physiological signal is transmitted first, followed by a lower embedding strength signal. In signal compression for medicinal purposes, specifically, when the signal is steganographed, the compression ratio is limited in order to uphold the clinical significance of the medical signal and prevent modifying its diagnostic construal [93].

$$\min \mathbb{D}_{JS^2}(R_{\text{Steg}}, R_S) \text{ subject to } R_{\text{Steg}} \text{ and } R_S \quad (2)$$

where $\mathbb{D}_{JS^2} = \mathbb{D}_{\text{Steg}} + \mathbb{D}_S$, $\mathbb{D}_{JS^2}$ is distortion due to *joint steganography-source coding* and $\mathbb{D}_S$ is distortion due to source coding. We start with a steganography embedding

rate $R_{\text{Steg}} \in (0, C_{\text{Steg}})$ and source coding rate $R_S \in (0, R_{\text{Budget}})$ such that $\mathbb{D}_{JS^2}$ is negligible. Hence, selection of pair; R_{Steg} and R_S plays a crucial role in JS^2C^2 scheme.

3.1.3 Rate-congruent channel coding

Diversity in importance between different JS^2 coded levels call UEP. In other words, different sections of the JS^2 bit-stream have different error sensitivities and hence deserve different degrees of protection. Rate-Compatible Punctured Turbo codes and LDPC codes are powerful techniques of UEP-based channel coding. However, we have applied RCPC codes due to its flexibility, efficacy, and practicality. A family of RCPC codes is generated from ordinary convolutional code, called a mother code, with channel code rate $R_C = 1/n$. Some output symbols of the mother encoder are punctured, which allows the construction of a family of codes with channel code rates: $p/np, p/(np-1), \dots, p/(p+1)$, where p is the puncturing period.

In RCPC, the coding rate is dynamically varying to satisfy both BER requirement and erratic channel condition:

- Lower the channel code rate better the BER performance, which implies the better quality of the signal. So, if higher-rate code does not offer sufficient protection, one can switch to a lower-rate code merely by the addition of extra redundancy.
- The adaptive part is that different coding rates for a different important part of the signal are attainable.
- Ability to perform cost-effective soft-decision decoding. The same Viterbi trellis can be used for all channel code rates.

The performance of RCPC, e.g., a convolutional code with a mother code rate of 1/2 may be punctured to a higher rate of, for example, 15/16 simply by a punctured convolutional code, generally scales well with the amount of parity transmitted. In addition, to limit the error propagation and error detection, CRC is used.

3.2 The holistic framework for joint steganography-source-channel coding scheme

Our intention is to perceive the optimal UEP arrangement for the steganographed physiological data communication. The joint methodology is exhibited in Fig. 3. Controller with knowledge of embedder's concealment strategy and channel status information, commands the joint scheme of steganography, source and channel coding specifically, joint rate allocation. This will minimize the expected end-to-end distortion. The formulation of JS^2C^2 problem: Steganographed physiological signal

Fig. 3 The JS^2C^2 : Joint steganography-source-channel coding scheme

with embedding rate R_{Steg} and a layered bit-stream with a source coding rate R_S with regulating channel rates R_C minimize joint reconstruction distortion $\mathbb{D}_{JS^2C^2}(R_{\text{Steg}}, R_S, R_C)$, subject to the total transmission rate constraint R_{Budget} .

$$\min \mathbb{D}_{JS^2C^2}(R_{\text{Steg}}, R_S, R_C) \text{ subject to } R_{JS^2C^2} \leq R_{\text{Budget}} \quad (3)$$

$$\text{and } R_{\text{Steg}} \leq C_{\text{Steg}},$$

where R_C is channel rate allocation vector. Distortion $\mathbb{D}_{JS^2C^2}$ at the receiver considers both, cover and stego distortion $\mathbb{D}_{C,S}$ and embedded and extracted data distortion $\mathbb{D}_{Em,Ex}$. There is a mutual connection between steganography, source, and channel coding as shown in Fig. 3. The extent of inserted secret data in steganography, not merely affect the host signal quality but also restrict the source coding and channel rate allocation. For example, a source coding degree, i.e., high compression, not only deteriorates the quality of the host signal but also has an adverse impact on the embedded information in the host signal. On the contrary, low compression not only disrupts the transmission efficiency but reliability as there are fewer bits for error correction and detection at the channel. Hence, R_{Steg} and R_S are regulated in such a manner that the *Joint Steganography-Source Coding* distortion $\mathbb{D}_{JS^2}$ is insignificant. Moreover, for the inadequate budget R_{Budget} , the total bits are distributed for source coding and channel coding. Consequently, to attain the best channel coder error protection and prevent critical variation at the output of the channel decoder, entered data at the source coder must not be compressed over a certain degree. For instance, if a higher rate is applied to source bits, the channel errors will destroy the physiological signal. In contrast, if a lower rate is applied to source bits, the restoration attribute will degrade due to the over quantization of the source data.

By carefully setting the embedding rate and compression rate in addition to variable-rate channel codes, all embedded data security, communication efficiency, and reliability may be uplifted due to the following reasons:

- Integration of our novel UES-based USE algorithm to UEP-based JSC^2 . USE's Embedding strength is assigned according to the significance of secret data.
- Wavelet-based compression algorithms generate embedded bit-streams with different position and magnitude with information in descending significance.
- Adequate bits for channel error correction and detection.

The entire bit-stream consists of the concatenation of all these independently protected layers. In short, steganography's security is sensitive to source-channel coder's rate selection and needs to be carefully set in control by appropriate allocation of steganography rate R_{Steg} , source coding rate R_S , and channel code rates R_C . Optimum selection of steganography and source-channel rates of our proposed JS^2C^2 scheme for efficient and reliable transmission of steganographed physiological signals over the noisy channel is discussed in the following section.

4 Problem setup, analysis of distortion at different stages, and optimization

Jointly source and channel coded (JSC^2) steganographed (JS^2C^2) signal

$$\begin{cases} \hat{\mathbb{P}}(t) = \mathcal{USE}_{\mathcal{M}}(\mathbb{P}(t), \mathbb{I}, \mathbb{K}) \\ \bar{\mathbb{P}}(t) = \mathcal{C}(\hat{\mathbb{P}}(t)) = \mathcal{C}(\mathcal{USE}_{\mathcal{M}}(\mathbb{P}(t), \mathbb{I}, \mathbb{K})) \\ \bar{\bar{\mathbb{P}}}(t) = \mathcal{C}(\bar{\mathbb{P}}(t)) = \mathcal{C}\{\mathcal{C}[\mathcal{USE}_{\mathcal{M}}(\mathbb{P}(t), \mathbb{I}, \mathbb{K})]\} \end{cases} \quad (4)$$

$\mathcal{USE}_{\mathcal{M}}$ is the *Unequal Steganography Embedding* algorithm and $\mathbb{K}$ is the secret key. $\mathbb{P}(t)$ is physiological signal and $\mathbb{I}$ is the secret data. The unequally steganographed physiological signal $\hat{\mathbb{P}}(t)$ is indistinguishable from original physiological signal $\mathbb{P}(t)$ and may be subjected to lossy compression $\mathcal{C}(\cdot)$ and channel coding $\mathcal{C}(\cdot)$. The embedded secret bits $\mathbb{I}$ are to be extracted from JS^2C^2 signal $\bar{\bar{\mathbb{P}}}(t)$.

4.1 Problem setup

The goal is to minimize the expected joint reconstruction distortion $\mathbb{D}_{JS^2C^2}(R_{\text{Steg}}, R_S, R_C)$ subject to the $R_{JS^2C^2}$, the joint steganography and JSC^2 rate for the total transmission rate constraint R_{Budget} . The JS^2C^2 problem formulated in the last section (Eq. 3)

$\min \mathbb{D}_{JS^2C^2}(R_{\text{Steg}}, R_S, R_C)$ subject to $R_{JS^2C^2} \leq R_{\text{Budget}}$
and $R_{\text{Steg}} \leq C_{\text{Steg}}$

Joint distortion $\mathbb{D}_{JS^2C^2}$ considers both, distortion between cover and stego and distortion between embedded and extracted data at the receiver. The noise due to processing of signal such as compression/decompression along with channel noise affects not only original cover signal $\mathbb{P}(t)$ but also the steganographed secret data $\mathbb{I}$. Let us assume the reconstructed corrupted host and secret data are $\tilde{\mathbb{P}}(t)$ and $\tilde{\mathbb{I}}$ respectively. In addition to minimizing $\mathbb{D}_{C,S}$, the error $\mathbb{D}_{Em,Ex} = \mathbb{I} - \tilde{\mathbb{I}}$ should be minimized and not exceed beyond certain value $\varepsilon_{\mathbb{D}_{C,S}}$ and $\varepsilon_{\mathbb{D}_{Em,Ex}}$ respectively to uphold the JS^2C^2 performance.

4.2 Distortion due to embedding

Steganography distortion includes both distortion between the cover and stego as well as distortion between embedded and extracted Data.

4.2.1 Cover and stego distortion

Let P is the length of the physiological signal, and MSE between cover and stego due to USE has been calculated as:

$$\mathbb{D}_{C,S,USE} = \frac{1}{P} \sum_{p=1}^P (\mathbb{P}(p) - \hat{\mathbb{P}}(p))^2 \quad (5)$$

The effectiveness of the USE technique can also be evaluated by distortion measurement by using WWPRD.

4.2.2 Embedded and extracted data distortion

Let S be the length of the steganographed secret data, and MSE between embedded and extracted secret data has been calculated as:

$$\mathbb{D}_{Em,Ex,USE} = \frac{1}{S} \sum_{s=1}^S (\mathbb{I}(s) - \hat{\mathbb{I}}(s))^2 \quad (6)$$

where $\hat{\mathbb{I}}$ is the extracted information of the proposed USE extractor.

4.3 Distortion due to joint steganography source coding

The problem of finding optimum joint steganography and lossy compression considers the search of minimum achievable compression rate $R_S \in (0, R_{\text{Budget}})$ as a function of the steganography rate $R_{\text{Steg}} \in (0, C_{\text{Steg}})$. The allowed average joint distortion $\mathbb{D}_{JS^2} \leq \varepsilon_{\mathbb{D}_{JS^2}}$ should be such that the average

probability of error in decoding of the steganographed data has been made reasonably small for sufficiently large block length. Suitable embedded source coders; e.g., SPIHT, by strategy, have excellent performance at all rates. JS^2C^2 is desirable for these coders in such a way that, in addition to having the best end-to-end performance for a given rate budget, the coder also attains good performance at intermediary rates. More details of JS^2C^2 are discussed in the following sub-section.

4.4 Distortion due to joint source-channel coding

Figure 4a demonstrates the packetization scheme of JS^2 bits along with JS^2C^2 packet structure Fig. 4b. Let us assume, the M layers JS^2C^2 system with the fixed coded packet length $\mathbb{L}_p$. Note that each layer is fully embedded, and no dependencies exist among layers. To implement UEP, first JS^2 sub-streams are partitioned into equal-length packets then error detection code CRC is attached. The unequal protection for the source packets is described by specifying a coding strategy $\mathbb{C}_{\mathcal{J}}$. A coding strategy $\mathbb{C}_{\mathcal{J}}$ assigns N channel codes to the M source packets out of the source coder. Let $R_C = \{R_C(c_{\mathbb{C}_{\mathcal{J}}}^1), R_C(c_{\mathbb{C}_{\mathcal{J}}}^2), \dots, R_C(c_{\mathbb{C}_{\mathcal{J}}}^N)\}$ be the rate allocation vector where: $R_C(c_{\mathbb{C}_{\mathcal{J}}}^1) < R_C(c_{\mathbb{C}_{\mathcal{J}}}^2) < \dots < R_C(c_{\mathbb{C}_{\mathcal{J}}}^N)$. Each of the M frames will be allotted a specific code rate $R_C(c_{\mathbb{C}_{\mathcal{J}}}^{n_m}) \in R_C$, $1 \leq n_m \leq N$ and $1 \leq m \leq M$. The normalized JS^2C^2 transmission rate $R_{JS^2C^2}$ for the coding strategy $\mathbb{C}_{\mathcal{J}}$ is given by [49]

$$R_{JS^2C^2} = \sum_{m=1}^M \frac{R_{S,m}}{R_C(c_{\mathbb{C}_{\mathcal{J}}}^{n_m})}, \quad (7)$$

where $R_{S,m}$ are source coder rates for $1 \leq m \leq M$.

d_m : After successfully decoding all packets up to packet m , the decoded signal will have a residual distortion.

P_m : Probability that the m th packet is erroneous after decoding. For total M channel packets, probability of error-free decoding of exactly m packets that is first decoding failure at packet $m + 1$ is

$$P_{m+1} \prod_{k=1}^m (1 - P_k) \quad m = 1, 2, \dots, M \quad (8)$$

Total expected distortion due to JS^2C^2 has been calculated as

$$\mathbb{D}_{JS^2C^2} = d_0 P_1 + \sum_{m=1}^{M-1} d_m \left(\prod_{k=1}^m (1 - P_k) \right) P_{m+1} + d_M \prod_{k=1}^M (1 - P_k) \quad (9)$$

Fig. 4 **a** Packetization of source-coded steganographed (JS^2) data **b** JS^2C^2 packet structure with UEP, channel coder parity bits: RCPC/CRC

We need to minimize the total JS^2C^2 distortion $\mathbb{D}_{JS^2C^2}$, subject to the constraint on the total bit rate.

$$\min \mathbb{D}_{JS^2C^2} \text{ subject to } R_{JS^2C^2} \leq R_{\text{Budget}} \quad (10)$$

$R_{JS^2C^2}$ is the total JS^2C^2 bit rate.

4.5 Total expected joint distortion and optimization formulation

Joint reconstruction distortion involves both cover-stego distortion and embedded-extracted data distortion:

- End-to-end JS^2C^2 MSE between P length original and reconstructed biosignal has been calculated as:

$$\begin{cases} \mathbb{D}_{C,S} = \frac{1}{P} \sum_{p=1}^P (\mathbb{P}(p) - \tilde{\mathbb{P}}(p))^2 \\ \mathbb{D}_{C,S} \leq \epsilon_{\mathbb{D}_{C,S}} \end{cases} \quad (11)$$

- End-to-end JS^2C^2 MSE between embedded and extracted secret data for S length steganographed secret data has been calculated as:

$$\begin{cases} \mathbb{D}_{Em,Ex} = \frac{1}{S} \sum_{s=1}^S (\mathbb{I}(s) - \tilde{\mathbb{I}}(s))^2 \\ \mathbb{D}_{Em,Ex} \leq \epsilon_{\mathbb{D}_{Em,Ex}} \end{cases} \quad (12)$$

Our proposed JS^2C^2 schemes objective is to find the best steganography rate R_{Steg} , source coding rate R_S , and rate-adaptable channel codes with emphasis on UEP for the communication of medical data. To be precise, JS^2C^2 offers a layered bit-stream of steganographed physiological signal that minimizes the expected joint reconstruction distortion subject to a total transmission rate constraint R_{Budget} .

We start with picking a steganography embedding rate $R_{\text{Steg}} \in (0, C_{\text{Steg}})$ and $R_S \in (0, R_{\text{Budget}})$ and then $R_C \in (0, R_{\text{Budget}})$ such that

$$\begin{cases} \min \mathbb{D}_{\text{Steg}}(R_{\text{Steg}}) \text{ subject to } R_{\text{Steg}} \leq C_{\text{Steg}} \\ \min \mathbb{D}_{JS^2}(R_{\text{Steg}}, R_S) \text{ subject to } R_{\text{Steg}} \text{ and } R_S \\ \min \mathbb{D}_{JS^2C^2}(R_S, R_C) \text{ subject to } R_{JS^2C^2} \leq R_{\text{Budget}} \\ \text{OR} \\ \min \mathbb{D}_{JS^2C^2}(R_{\text{Steg}}, R_S, R_C) \text{ subject to } R_{JS^2C^2} \leq R_{\text{Budget}} \end{cases} \quad (13)$$

The challenge is to find an optimal rate allocation scheme that minimizes each term of equation (13) individualistically. One possible way to find the optimal rate allocation is by doing an exhaustive search. However, for large packet sizes, the complexity of the scheme is very high and infeasible. In the next sub-section, we have proposed an efficient optimization scheme for JS^2C^2 rate allocation.

Algorithm 3 The JS^2C^2 -Optimization Pseudo-Code

- First, randomly generate a number of individual solutions to form an **initial population**. Here, one solution means one possible allocation of rates. For the embedding capacity C_{Steg} , steganography rate $R_{Steg} \in (0, C_{Steg})$, source rate $R_S \in (0, R_{Budget})$ and **channel code rate allocation vector** R_C .
- Second, initialize the starting point population and calculate the **fitness** of each solution based on the equation below so that each individual solution contributes to an average end-to-end distortion value.

$$\begin{cases} \min \mathbb{D}_{Steg}(R_{Steg}) \text{ subject to } R_{Steg} \leq C_{Steg} \\ \min \mathbb{D}_{JS^2}(R_{Steg}, R_S) \text{ subject to } R_{Steg} \text{ and } R_S \\ \min \mathbb{D}_{JS^2C^2}(R_S, R_C) \text{ subject to } R_{JS^2C^2} \leq R_{Budget} \end{cases}$$

- Third, after **fitness** value calculation, choose half of the population that has the lower end-to-end distortion to form the parent pool. From this pool, two ‘parents’ are selected to produce new offsprings through **crossover** and **mutation** operations. Two offsprings will be generated. However, only offspring satisfying non decreasing channel code rates are retained.

$$\min \mathbb{D}_{JS^2C^2}(R_{Steg}, R_S, R_C) \text{ subject to } R_{JS^2C^2} \leq R_{Budget}$$

The overall bit rate $R_{JS^2C^2}$ does not exceed R_{Budget} while minimizing the overall end-to-end distortion $\mathbb{D}_{JS^2C^2}$.

Channel code rate allocation vector

$$R_C = \{R_C(c_{\mathcal{S}}^1), R_C(c_{\mathcal{S}}^2), \dots, R_C(c_{\mathcal{S}}^N)\}$$

$$\text{Overall Bit Rate } R_{JS^2C^2} \triangleq \sum_{m=1}^M \frac{R_{S,m}}{R_C(c_{\mathcal{S}}^{n_m})}$$

$$R_C(c_{\mathcal{S}}^{n_m}) \in R_C, 1 \leq n_m \leq N \text{ and } 1 \leq m \leq M$$

$$R_C(c_{\mathcal{S}}^1) \leq R_C(c_{\mathcal{S}}^2) \leq \dots \leq R_C(c_{\mathcal{S}}^N), \\ 1 \leq n_m \leq N, m = 1, 2, \dots, M$$

(a)

Lower code rates are devoted to more important packets. The constraint (a) tells us that in each packet, the lower scalable layers make more sense for reconstruction.

- As ‘parents’ with high fitness values have more chances to be used, the created new offspring typically share good features of their ‘parents’.
- Finally, with this process, the average fitness value will increase in general, i.e., the corresponding distortion will be decreased. This process is repeated until a termination condition has been reached.

4.6 The JS^2C^2 -optimization

In the last sub-section, an analytical distortion model for JS^2C^2 system is built and an optimization problem is formulated. The global optimal assignment of the problem (13) seems to be computationally prohibitive in a realistic system, especially in the case of the huge number of scalable layers in each frame. There are various techniques, such as gradient descent, dynamic programming, hill climbing, etc. for the optimization of composite systems. However, GAs [94] are mathematically motivated search techniques that try to emulate evolutionary processes to solve optimization problems. Instead of searching one point at a time, it uses multiple search points through phases of evolution, crossover, mutation, and selection repeatedly. The optimization technique attempt to find near-optimal solutions without going through an exhaustive search thus results in a reduction of search space and time.

In our approach, the multiple search points can converge to near-optimal solutions for joint rate allocation with an accelerated computational scheme. The JS^2C^2 model’s optimization workflow is depicted in Fig. 5 and pseudo-code is exhibited in Algorithm 3. By using JS^2C^2 -optimization, one can easily create a near-optimal rate allocation of R_{Steg} , R_S , and channel code rate allocation vector R_C for the given rate budget R_{Budget} through crossover and mutation operations, to achieve minimum end-to-end JS^2C^2 distortion.

5 Experimental results and discussion

This section provides the experimental results and analysis of the proposed JS^2C^2 scheme. This work is simulated in MATLAB R2018a (Version 9.4.0). First, we studied deep CNN-based ECG classification by using an existing pre-trained NN model then cover-stego correlation and wavelet-based distortion are calculated and compared for our USE and three embedding models. Furthermore, to evaluate the communication performance, we have considered our proposed JS^2C^2 system with Binary Phase-Shift Keying (BPSK) modulation over the Additive White Gaussian Noise (AWGN) channel. However, our model can be easily extended to other physiological signals and more complex channel models. JS^2C^2 performance is analyzed in terms of quality metrics, such as WWPRD, correlation, PSNR and MSE. Moreover, the transmission energy consumption of USE-based and conventional ESE-based framework is compared.

Fig. 5 The JS^2C^2 -optimization workflow: choose optimum values of R_{Steg}/R_s /vector R_c to minimize end-to-end distortion $D_{JS^2C^2}$

5.1 Data description

ECG data are obtained from groups of people: persons with normal sinus rhythms (NSR), persons with cardiac arrhythmia (ARR), and persons with congestive heart failure (CHF), and so on. In total, 412 persons ECG signal of length 10 s from four PhysioNet databases are used in the analysis (listed in Table 1). With 162 persons ECG from normal, arrhythmia, and CHF records from MIT-BIH ECG databases are used for deep CNN-based ECG classification (shown in Fig. 6). The PTB diagnostic ECG database contains 549 records from 290 subjects (aged 17–87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6) suffering from different heart disorders such as 148 subjects suffering from myocardial Infarction, 52 health controls, 18 cardiomyopathy/heart failure, 15 bundle branch block, 14 dysrhythmia, 7 myocardial hypertrophy, 6 valvular heart disease, 4 myocarditis, and 4 miscellaneous. Randomly picked 250 subjects ECG from the PTB diagnostic ECG database are used for wavelet-based distortion and correlation calculations.

5.2 Deep convolutional neural network for ECG classification

In various DL applications, a sufficient amount of training data is not available, and synthesizing new realistic training examples is not feasible. In these cases, leveraging existing NNs that have been trained on large data sets for conceptually similar tasks is desirable. This leveraging of existing NNs is called transfer learning. GoogLeNet is one of the key CNN models for vision computing due to its fewer neurons, small-scale parameters, low model

Fig. 6 Class of ECGs used for the CNN training from different data-bases mentioned in Table 1

complexity, and outstanding performances. There are other existing pre-trained deep CNN, such as AlexNet, SqueezeNet can also be used. In brief, since training a deep CNN from scratch is computationally expensive and requires a large amount of training data, we used deep CNN GoogLeNet for ECG signal classification by using transfer learning and the Continuous Wavelet Transform (CWT). Figure 7 shows 144 layers CNN validation accuracy for ECG classification based on a time-frequency representation. The time-frequency representations of the ECG signals called scalograms are created which is the absolute value of the CWT coefficients of a signal. Images are randomly divided into two groups, one for training and the other for validation. 80% of the images are used for training, and the remainder for validation e.g., 130 images out of 162 for training and 32 images for validation. This simulation requires MATLAB deep learning toolbox. The CNN achieves validation accuracy $> 96.5\%$ for classifying the ECG into three categories i.e., Normal Sinus Rhythm, Arrhythmia, and Congestive Heart Failure.

Table 1 Data description

Database	Heart Condition	Subjects
MIT-BIH normal sinus rhythm database [95]	Normal	36
MIT-BIH arrhythmia database [95]	Arrhythmia	96
The BIDMC congestive heart failure database [95, 96]	Congestive heart failure	30
PTB diagnostic ECG database [95, 97]	Myocardial infarction, cardiomyopathy/heart failure, bundle branch block, dysrhythmia, myocardial hypertrophy, etc.	250

Fig. 7 The 144 layers convolutional neural network validation accuracy for ECG classification

5.3 Embedding distortion measurement

The effectiveness of the proposed USE technique is evaluated by distortion measurement by using WWPRD. WWPRD is calculated by summing different sub-band distortions weighed with a corresponding normalized coefficient, which is defined as follows [98]:

$$WWPRD = \sum_{j=0}^{j=N_L} w_j \cdot WPRD_j \quad (14)$$

where N_L is the total number of sub-band and w_j is the normalized sum of wavelet coefficients in j th sub-band can be calculated by dividing the sum of the absolute value of coefficients within that band by sum of the absolute value of wavelet coefficients in all the bands.

$$w_j = \frac{\sum_{k=1}^{K_j} |C_j(k)|}{\sum_{j=0}^{N_L} \sum_{k=1}^{K_j} |C_j(k)|} \quad (15)$$

$WPRD_j$ is the normalized root-mean-square difference between the original wavelet coefficients and reconstructed wavelet coefficients calculated by

$$WPRD_j = \sqrt{\frac{\sum_{k=1}^{K_j} (C_k - \hat{C}_k)^2}{\sum_{k=1}^{K_j} C_k^2}} \quad (16)$$

where C_k are the original coefficients and $\hat{C}_k$ are stego-graphed coefficients within the sub-band j .

A comparison is created between our USE-based USE where secret data is embedded in DWT-level 3 detail coefficients with multi-embedding strength and three embedding models: *Single-Embedding Strength-Lvl3* (secret data embedded into DWT-level 3 detail coefficients with single-embedding strength called ESE), *Single-Embedding Strength-Lvl2* (secret data embedded into DWT-level 2 detail coefficients with single-embedding strength), *Double Embedding Strength-Lvl2* (secret data embedded into DWT-level 2 detail coefficients with double-embedding strength) shown in Fig. 8. For PTB Diagnostic ECG Database's 250 patient's single-lead ECG (lead II), USE WWPRD is compared with all three models WWPRD and USE always attains lower WWPRD as shown in Fig. 8. Our proposed USE technique offers high-security protection for patient's confidential data with very low distortion (less than 0.5%) as illustrated in Fig. 8. Additionally, cover and stego correlation with and without noise is also portrayed in Fig. 9, in which it is clear that for 40 dB SNR, cover-stego correlation is beyond 95%. Consequently, ECG data remains diagnosable after steganography. Furthermore, the correlation between extracted and embedded data is relatively high for USE as compared to ESE as shown in Fig. 10.

Fig. 8 250 Patient's ECG WWPRD comparison between proposed USE and three embedding models

5.4 Cover and stego correlation and distortion

Figure 11 shows wavelet-based compression algorithms PSNR with respect to steganography rate for JS^2 coder stage. In Fig. 11, for the given R_{Steg} , at low R_s , PSNR value is low. Moreover, from Fig. 11, it can be inferred that there is a dramatic increase in PSNR value from around 17 dB ($R_s = 1$ bpp) to approximately 27 dB at $R_s = 2$ bpp. The higher the PSNR, the better the quality of the signal. Figure 11 is also pretended as JS^2 with AWGN channel errors. In our simulation, for different value of R_{Steg} with R_s (for example $R_s = 2$ bpp), the noise of 25 dB and 35 dB are introduced, as shown in dashed lines in Fig. 11. So, AWGN will deteriorate the JS^2 performance, hence channel coding is required to handle channel errors. Figures 12, 13 and 14 present JS^2 correlation, JS^2C^2 correlation and end-to-end JS^2C^2 distortion $\mathbb{D}_{JS^2C^2}$, respectively. These figures unfold the facts that as R_{Steg} increases, source coder PSNR decreases as shown in Fig. 11. To maintain SNR (signal quality) at the source coder, if the

compression rate is increased, a higher correlation can be achieved as exhibited in Figs. 12 and 13. Moreover, as shown in Fig. 13, the achieved correlation for a given source coder rate is almost independent of the number of steganographed bits. Hence, in our JS^2C^2 framework, embedding capacity can be improved without affecting the correlation between cover and stego for the given R_s . However, to achieve high correlation if the source coding rate increased, there will be fewer bits for error protection (parity bits) at the channel coder (SNR decreases).

In Fig. 14, end-to-end JS^2C^2 distortion is rising as R_{Steg} increasing as portrayed. Moreover, Fig. 14 substantiates that increment in R_s causes decrement in distortion. Hence, the higher the compression rate better the JS^2C^2 quality. Thus, low R_s not only affects the quality of JS^2C^2 signal but also the embedded data as represented in Table 2, where MSE is higher, which is undesirable to avoid incorrect diagnosis. From the aforementioned figures, it is clear that there should be a compromise between steganography rate and compression rate in

Fig. 9 USE: correlation between cover and stego

Fig. 10 USE versus ESE: correlation between embedded and extracted data in the presence of AWGN

Fig. 11 JS^2 : source coder PSNR versus steganography rate

Fig. 13 JS^2C^2 correlation between cover and stego signal w.r.t. embedding rate

Fig. 12 JS^2 correlation between cover and stego w.r.t. source coding rate

order to achieve both moderate embedding capacity as well as efficiency. The JS^2C^2 -optimization's attempt to find a near-optimal combination of R_{stego} and R_s without going through an exhaustive search.

5.5 Embedded and extracted data correlation and distortion

In Fig. 15, the correlation between embedded and extracted data starts decreasing as steganography rate is increasing. Furthermore, MSE between embedded and extracted data at $R_s = 2$ bpp is lesser as compared to the lower value of R_s shown in Fig. 16. This ensures

that diagnosis is possible with a steganographed medical signal and confidential information can be retrieved successfully at $R_s \geq 2$ bpp as shown in Fig. 17.

5.6 Channel coder performance

Utilizing knowledge about the channel is vital for effective and reliable communication. Although we use the RCPC codes for channel coding, our JS^2C^2 system can be easily extended to other powerful variable-rate channel codes, such as Turbo codes, LDPC codes. To evaluate the performance of JS^2C^2 system, we consider AWGN channel and BPSK modulation/demodulation. RCPC channel code with the generator polynomial (133, 171), mother code rate 1/2, with different puncturing patterns are simulated. Set of RCPC codes is {0.5, 0.57, 0.67, 0.75, 0.8, 0.83, 0.86}.

To obtain rate compatibility, lower-rate code can be obtained by higher-rate codes by the addition of extra redundancy. We can observe in Fig. 18, E_b/N_o vs. BER for different channel code rates substantiates that the error protection level is consistently reducing as the code rates increase. In other words, the lower-rate code gives the better BER performance as compared to the higher-rate codes. In Fig. 18, Channel coding rate R_c vs. BER for the different E_b/N_o is also plotted. Figure 18 depicts that for the given E_b/N_o , the BER performance gets worse with the increase in channel coding rate R_c .

5.7 Energy consumption comparison

Figure 19 illustrates the relationship between expected transmission energy consumption and the expected

Fig. 14 JS^2C^2 mean-square error between original and reconstructed ECG $R_{Steg1} < R_{Steg2} < R_{Steg3} < R_{Steg4}$

Table 2 End-to-end MSE between embedded and extracted data $R_{Steg1} < R_{Steg2} < R_{Steg3} < R_{Steg4}$

$R_{Steg} \rightarrow R_s$	R_{Steg1}	R_{Steg2}	R_{Steg3}	R_{Steg4}
0.5 bpp	1.7778	1.7778	2.1212	2.3030
1.0 bpp	0.8889	1.4444	1.8182	1.7879
1.5 bpp	0.4444	0.4444	0.4242	0.3939
2.0 bpp	0.0000	0.0000	0.0000	0.1515
2.5 bpp	0.0000	0.0000	0.0000	0.0000
3.0 bpp	0.0000	0.0000	0.0000	0.0000

distortion (MSE between cover and stego). We compare our proposed USE-based steganography USE with source coding (JS^2) with EES-based steganography ESE with source coding. We assumed that transmitter need $5 \mu J$ energy per bit. For example, in Fig. 19, both approaches have the same expected distortion (200 MSE), but the USE-based approach has an expected transmission energy consumption that is less than half of the energy consumed in ESE-based approach i.e., approximately 55% smaller. However, different amounts of distortion will have a different set of energy savings.

Moreover, when USE-embedded and source-coded bit-stream is unequally error protected at the channel coder, it further improves energy. UEP at channel coder optimizes the different RCPC distortion reduction of ECG data by adaptively assigning codes to protect the different

Fig. 15 Correlation between embedded and extracted information w.r.t. embedding rate

parts of compressed ECG data. Our group demonstrated that *Rate-switching Unequal Protection* (RUEP) mechanism provides an improved communication energy efficiency by at least 45% compared with traditional schemes in the AWGN channel [60]. On the other hand, when the ESE-based approach's higher energy requirement for the same distortion is equally error protected (EEP) at the channel

Fig. 16 Mean-square error between embedded and extracted information w.r.t. embedding rate

Fig. 18 BER Performance of channel coder: **a** E_b/N_o versus BER, **b** channel Rate R_c versus BER

Fig. 17 Embedded and extracted data MSE w.r.t. source coding rate

Fig. 19 Energy consumption comparison for USE and ESE-based approach

coder will further make it energy inefficient. Therefore, our proposed JS^2C^2 framework not only achieves energy efficiency due to our UES-based USE but also because of the UEP scheme at the channel coder.

6 Conclusions and summary

Integration of novel UES-based steganography and UEP-based JS^2C^2 for the progressive transmission of physiological signals over noisy channels is proposed. The uniqueness lies in the innovative JS^2C^2 approach where the wireless physiological signals transmission does not rely

on explicit codes for either steganography, source coding or channel coding; instead, it directly maps the raw physiological signal values to the complex-valued channel input symbols. Moreover, it provides much higher efficiencies in transmission by saving energy while preserving the medical signals. In our UES-based embedding scheme, the most important secret data will have higher embedding strength and will be transmitted at the beginning followed by intermediate ones and then least important secret data with least embedding strength. In progressive transmission, when the compression is applied, it affects the embedded bit-stream based on reverse significance means the least important information with least

embedding strength which is at the back of embedded bit-stream will be compressed first followed by intermediate ones and then the most important information with higher embedding strength. Since USE assigns unequal embedding strength based on importance and achieves very low distortion ($WWPRD < 0.5\%$), higher compression can be applied to save more energy without affecting the quality of cover with embedded data in it. On the other hand, low compression would not only affect the communication efficiency but also reliability as there are a fewer number of bits for channel error correction and detection. Hence, USE's embedding rate and source coding rate are attuned in such a way that the joint distortion due to steganography and source coding is negligible. Our simulation clearly shows that our proposed JS^2C^2 approach contributes significantly to lowering the end-to-end MSE distortion of steganographed physiological signal. By carefully setting the embedding rate and compression rate in addition to variable-rate channel codes, embedded data security along with communication efficiency and reliability can be uplifted. Furthermore, based on steganography, source, and channel coder statistics, the proposed algorithm JS^2C^2 determines the optimum rate distribution for communication. A low-complexity CNN-based ECG classification algorithm along with its secure and energy-efficient $Neural JS^2C^2$ transmission for real-time monitoring has been realized. The optimal parameters for our united framework have been calculated by JS^2C^2 -optimization method. Since the choice of those parameters is limited and exhaustively listed, they are calculated with either the simple optimization which supports large scalability as well as error-resilient code streams of physiological signal or any other complex optimization method, but would not affect the performance of real-time JS^2C^2 transmission schemes. In conclusion, by JS^2C^2 that matches the source effective rate-distortion to the channel code rate and channel condition, taking steganography rate into consideration, the performance of progressive transmission of the medical signal has been excelled with communication energy being saved by 55% in typical application scenarios.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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